Ecological traffic management: A review of the modeling and control strategies for improving environmental sustainability of road transportation

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Abstract

As road transportation energy use and environmental impact are globally rising at an alarming pace, authorities seek in research and technological advancement innovative solutions to increase road traffic sustainability. The unclear and partial correlation between road congestion and environmental impact is promoting new research directions in traffic management. This paper aims to review the existing modeling approaches to accurately represent traffic behavior and the associated energy consumption and pollutant emissions. The review then covers the transportation problems and control strategies that address directly environmental performance criteria, especially in urban networks. A discussion on the advantages of the different methods and on the future outlook for the eco-traffic management completes the proposed survey.

Keywords: energy efficiency, traffic management, traffic modeling, pollutant emissions, optimization.

1. Introduction

While energy-related air pollution is considered today one of the primary premature death causes (World Health Organization, 2016), the global carbon dioxide (CO_2) emissions are on a rising trend destined to grow well above the levels imposed by the international climate goals (International Energy Agency, 2018). Population surge and economic growth of the developing countries have been identified as the main causes of the drastic increase of energy demand and pollutant emissions in all sectors (International Energy Agency, 2018).

The worldwide transportation sector alone accounts for 55% of the total liquid fuels consumption and, with the increasing travel demand, this share is not expected to decrease for the next two decades (U.S. Energy Information Administration, 2017a). In the member countries of the Organisation for Economic Co-operation and Development (OECD), projections show that the improved energy efficiency in transportation may lead to a net decline of about 2% in energy use until 2040, thus outpacing the predicted increase of vehicle-miles traveled (VMT). However, in OECD-Europe, transportation still represents the biggest source of carbon emissions (Transport & Environment, 2018), contributing about 25% of the total CO_2 emissions, with cars and vans representing more than two thirds of this share (Mandl and Pinterits, 2018). The situation is even more alarming in non-OECD countries, where the transportation energy demand is expected to rise by 64% until 2040, implying an increase of about 15% of energy-related CO_2 emissions (U.S. Energy Information Administration, 2017a).

Therefore, a lot of attention has been drawn worldwide to finding the most effective measures to help reduce the current contribution to greenhouse gas emissions from transportation. Governments, practitioners and researchers seem to agree on the fact that a combination of short-term and long-term strategies must be adopted. In the short-term, policies and regulations encouraging changes in behavior and travel habits represent a key lever. Attractiveness of alternative means of transportation should be enhanced, a shift to less polluting transport modes should be promoted, and a change in purchasing habits favoring smaller and more energy-efficient cars should be encouraged (Chapman, 2007). In the long-term, the widespread adoption of innovative technological solutions such as electrification, connectivity and automation are expected to enable a significant shift in the future of personal transportation and mobility. The way for such a technological transformation of mobility is already being paved thanks to the diffusion of connected and automated vehicles (CAVs), multi-vehicle (V2V) and vehicle-infrastructure (V2I) cooperation and communication networks, in- and over-roadway sensors, cloud-computing capabilities, etc. (Guanetti et al., 2018).

However, the potential energy benefits of these technologies remain uncertain, mostly because of the high level of non-linear dependence between different aspects of an automated transportation system operating with conventional vehicles, as well as possible side-effects of automation (U.S. Energy Information Administration, 2017b). Among the features enabled by the aforementioned technologies that promise to increase energy efficiency and reduce pollutant emissions of transportation, it is worth mentioning eco-driving, eco-routing, platooning, roadway throughput optimization, powertrain electrification, vehicle down-sizing, parking search time reduction, ride-sharing. On the other hand, as for the side-effects that may endanger

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energy efficiency and emission reduction, it is likely that technology may increase traffic congestion as a consequence of an increased access to mobility, increase travel speeds as a consequence of enhanced safety, increase commute distances as an effect of increased comfort and reduced travel costs, etc. (U.S. Energy Information Administration, 2017b).

From a single-vehicle efficiency perspective, research suggests that lightweight, low-speed, autonomous vehicles have the potential to achieve fuel economies an order of magnitude higher than current cars (U.S. Energy Information Administration, 2017b). However, at system-wide level, current estimates suggest that the total energy consumption impacts can range from a 90% decrease to a 200% increase in fuel consumption as compared to a projected 2050 baseline energy (Brown et al., 2014).

Such a large variability in the possible outcome of the adoption of the new vehicular and traffic technologies makes it somewhat difficult to focus and prioritize the research efforts to increase energy efficiency of mobility. Nowadays, the general trend in research and policy seems to aim to reduce CO_2 emissions by pushing for more efficient vehicles and reducing VMT. This is based on a generally accepted paradigm that congestion mitigation programs should reduce CO_2 emissions. However, it is difficult to prove a clear direct proportionality between congestion and CO_2 emissions (Fiori et al., 2018). The most reliable approach to improve energy efficiency and reduce pollutant emissions in the design of a traffic regulation measure consists in directly considering these aspects as decision and optimization criteria. Therefore, interest in transportation regulation problems with explicit environmental considerations is growing (Wang et al., 2018; Vreeswijk et al., 2013).

This paper surveys the existing scientific literature on energy consumption and emission models, as well as road transportation problems directly addressing the issue of energy consumption and pollutant emissions reduction. Such problems can be tackled at different levels depending on the granularity and the object of the control action. At vehicle level, the energy-efficient control strategies typically act on single vehicles or groups of cooperating vehicles by modifying their individual speed profiles or route choices. At traffic level, the control strategies aim to influence the vehicular flow as a whole by acting on the typical flow regulation actuators, such as traffic lights, speed limits, etc. The adopted categorization in terms of modeling and control approaches both at vehicle and traffic level for the general problem of reducing environmental impact of road transportation is illustrated in Fig. 1.

The contributions of this paper are summarized as follows:

- A comprehensive literature review of the existing energy consumption and pollutant emissions models is provided. The review distinguishes between data and physics-based models and discusses their adaptation for usage with both single-vehicles and traffic flow.
- An overview of the existing vehicle and traffic control strategies to improve energy and environmental efficiency of transportation is given. The review focuses on the control techniques that explicitly address energy consumption and emissions. The connection and interaction between traffic congestion and energy efficiency is also discussed.
- As an outcome of this review, research gaps in the current state of the art have been identified and discussed in order to inspire future works in this field.

The body of the paper is organized as follows. Section II presents the energy consumption and emission models for the single vehicle with a brief discussion of how the vehicle kinematics can be obtained. Analogously, Section III introduces the modeling approaches to describe traffic kinematics, with a particular focus on the most popular fluid-dynamics traffic models, as well as the energy consumption and emission models for vehicular flow. The energy-optimal control strategies for single vehicles are presented in Section IV, while the transportation problems dealing with traffic energy efficiency are reviewed in Section V. Finally, Section VI contains concluding remarks and discussion on the current research gaps and future outlooks.

2. Emission and energy consumption models for single vehicles

Different models estimating emissions and energy consumption rate (J_y) of a vehicle as a function of its parameters and operation variables (u) have been investigated in the past. This section presents the data-driven and the physical modeling approaches employed to estimate J_y.

In the proposed formalization, J_y refers to the prediction of the rate of y, which can be calculated per distance traveled by the vehicle (J_y^{spat}) or per time unit (J_y^{temp}), depending on the modeling method. y corresponds either to the emission of a pollutant (CO, NOx, HC, ...) or the energy consumption (fuel or electricity consumption, depending on the vehicle powertrain considered):

$$y \in \{ \text{fuel or electricity consumption, emission of CO, NOx, HC, ...} \}$$

Such emission and energy consumption models are said microscopic because they consider each vehicle individually. They can be described as

$$J_y = f(u) \tag{1}$$

where f is a function that relates the model inputs to the output.

The function f can be constructed in different ways. The different approaches detailed in this section to estimate emissions and energy consumption are classified as illustrated in Fig. 2.

The first step to determine the emission and energy consumption rates of a vehicle is to determine its operation variables (e.g. speed, acceleration). A solution is to obtain these data by sensors. For example, Thibault et al. (2016) propose to use smartphone devices and their embedded sensors to get the position and speed of vehicles. Treiber and Kesting (2013b)

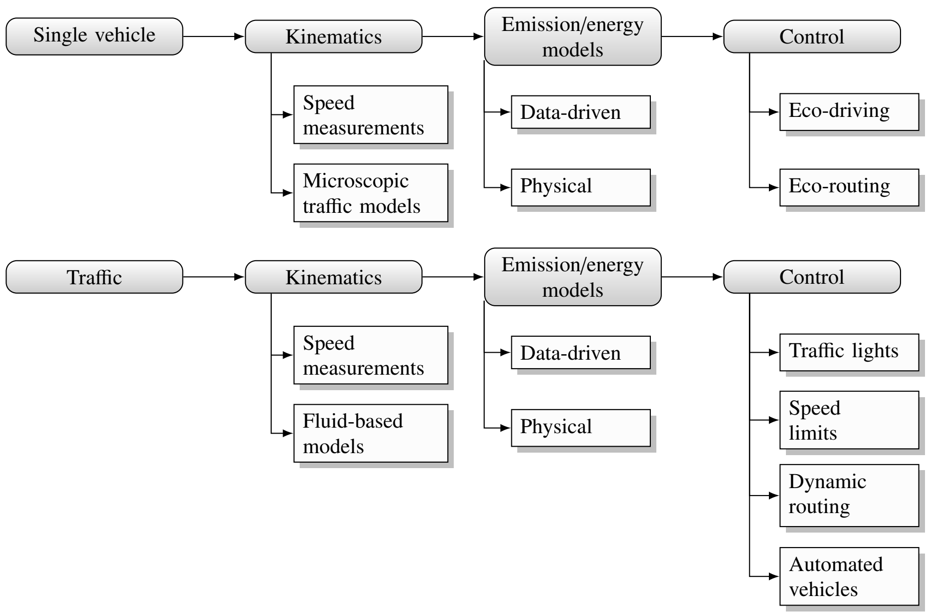

Figure 1: Diagram of the global approach for energy consumption and emissions modeling and control for single vehicles and traffic flow.

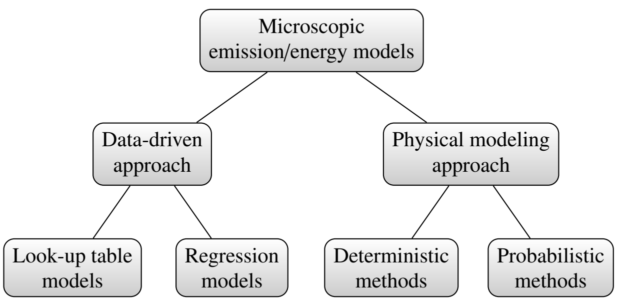

Figure 2: Classification of emission and energy consumption models for single vehicles.

present a methodology to express the operation variables of vehicles from trajectory and floating-car data.

They can also be determined through simulation using a microscopic traffic model, which reproduces the movement of each vehicle individually. Some complete overviews of microscopic traffic models can be found in van Wageningen-Kessels et al. (2015); Ferrara et al. (2018b); Hoogendoorn and Bovy (2001). These approaches are mainly based on the car-following principle (e.g. safe-distance models, stimulus-response models, action point models). For example, the optimal velocity car-following model expresses the acceleration of each vehicle as

$$a = \frac{v_e - v}{\tau} \tag{2}$$

where the optimal speed, v_e, depends on the distance with the vehicle upstream, and τ is the driver reaction time.

The use of a microscopic traffic model, especially in order to estimate emissions and energy consumption, requires a precise calibration of model parameters. Jie et al. (2013) present a methodology to perform such a parameters calibration and emphasize on its benefits in terms of speed and acceleration estimation.

The second step to determine the emission and energy consumption rates of a vehicle is to use a microscopic emission and energy consumption model whose inputs are the vehicle operating variables and parameters, summarized in Table 1. This step is presented in detail in the following sections.

2.1. *Data-driven methods*

Emission and energy consumption rates can be calculated using data-driven approaches. These can be either based on look-up table models or regression models.

2.1.1. *Look-up table models*

One old common approach to estimate emission and fuel consumption rates consists in performing chassis dynamometer tests and recording the emissions and fuel consumption in a look-up table, also called emission matrix. Usually, such look-up tables provide J_y from speed and acceleration (Post et al., 1984; Sturm et al., 1998) for a given set of vehicle parameters. These reference emission look-up tables can be used later to instantly estimate emissions and fuel consumption.

Although this method is easy to use, usually the available matrices are sparse, due to measurement difficulties. Moreover, empirical matrix-based prediction concerns only steady-state emissions, and not transient operations (Scora and Barth, 2006). Finally, this method is sensitive to the driving cycle and the quality of on-line measurements. This may lead to large errors.

Another possibility is to determine emission and fuel consumption rates as a function of the vehicle position. Andersen et al. (2013) propose to associate to each road a corresponding fuel consumption, based on average measurements. The amount of fuel consumed by a vehicle during a trip is therefore

Symbol	Description
a	Vehicle acceleration [m s^{-2}]
A	Cross-sectional area [m^2]
b	Stoichiometric CPF (Catalyst Pass Fraction) coefficient [s kg^{-1}]
c	Enrichment CPF coefficient [s kg^{-1}]
C_a	Aerodynamic drag coefficient [–]
C_d	Reynolds coefficient [–]
C_e	Engine friction factor [J rev^{-1} m^{-3}]
C_r	Rolling resistance coefficient [–]
COC	Center of combustion (50% energy conversion, from Top Dead Center) [crank angle degree]
CPF_y	Catalyst pass fraction of y [–]
d	Mass density of air [kg m^{-3}]
D	Engine displacement [m^3]
g	Gravitational constant [m s^{-2}]
LHV_fuel	Fuel lower heating value [J kg^{-1}]
m_cyl	In-cylinder air mass per stroke and displaced volume [kg m^{-3} sr^{-1}]
m_{O_2}	In-cylinder oxygen mass per stroke and displaced volume [kg m^{-3} sr^{-1}]
M	Vehicle mass [kg]
n	Engine speed [rev s^{-1}]
P_acc	Engine power demand associated with accessories [W]
R_BGR	In-cylinder burnt gas ratio [–]
v	Vehicle speed [m s^{-1}]
ϵ_y	Maximum catalyst efficiency of y [–]
α	Road grade angle [rad]
λ	Ratio between the air/fuel ratio at stochiometry and the commanded air/fuel ratio [–]
η_batt	Battery efficiency [–]
η_eng	Engine efficiency [–]
η_tf	Efficiency of the transmission and final drive [–]

Table 1: Parameters and operation variables of vehicles used in the emission and energy consumption models.

simply approximated by the sum of the average fuel consumption associated with the corresponding roads. This approach is very simple but it cannot distinguish between different types of vehicle, as they are all mixed in the same computed average value. Also, it cannot reflect the evolution of emissions and fuel consumption in case of traffic congestion.

2.1.2. Regression models

Emissions and energy consumption of a single vehicle can also be predicted on a second-by-second basis by using data-based models, such as regression techniques or neural networks. The inputs of these models can typically be the speed, acceleration or power demand, and the outputs are the emission or energy consumption rates prediction.

Regression techniques and neural networks for emission and energy consumption modeling both use the collected data in order to train a model that mimics these data. In regression techniques, it is necessary to identify the model parameters by curve fitting, while in neural networks the weight of the connections between neurons is to be identified.

The use of neural networks to estimate emissions and energy consumption is motivated by the heavy nonlinearity of emissions. There is also a need of high computational efficiency in order to be compatible with second-by-second microscopic traffic models. Such neural network frameworks can be found in Ahn (1998); Obodeh and Ajuwa (2009); Jafarmadar (2015); Xu et al. (2017).

Ahn (1998) presents non-linear multiple regression models constructed with quadratic and cubic speed-acceleration terms. The data used to determine the coefficients of these models for a given type of vehicle is obtained from dynamometer emission tests, based on the New European Drive Cycle (NEDC) (Ahn et al., 2004). It is also desirable to use data from vehicles in real urban traffic situations, when available (Panis et al., 2006). In fact, it is important to note that emission levels obtained from dynamometer tests can be much lower than those produced in real traffic (Pelkmans and Debal, 2006). For example, a criticism against the NEDC is that its acceleration profile is very smooth and not sufficiently realistic (Andre and Pronello, 1997).

Based on this technique, the VT-micro model can be formulated in matrix form (Zegeye et al., 2013) as

$$\ln(J_y^{\mathrm{temp}}) = \vec{v} M_y \vec{a} \tag{3}$$

where M_y denotes the regression coefficients matrix of y for the type of vehicle under consideration, $\vec{v}$ and $\vec{a}$ are respectively the speed and acceleration vectors defined as

$$\begin{aligned} \vec{v} &= \left[1,\ v,\ v^2,\ v^3\right] \\ \vec{a} &= \left[1,\ a,\ a^2,\ a^3\right]^T \end{aligned} \tag{4}$$

Note that the VT-micro model can also be expressed with a regression coefficients matrix for positive accelerations, and another matrix for negative accelerations, depending on the data used to calibrate the model (Alsabaan et al., 2012). VT-micro estimates emissions and energy consumption from instantaneous speed and acceleration, i.e. measured at the present time. Qi et al. (2004) formulate a regression model, named POLY, which also takes into account the past accelerations and the road grade angle. The model reads

$$\begin{aligned} J_y^{\mathrm{temp}} \;=\;& \beta_0 + \beta_1 v(k) + \beta_2 v^2(k) + \beta_3 v^3(k) \\ & + \beta_4 T^{\mathrm{acc}}(k) + \beta_5 T^{\mathrm{dec}}(k) \\ & + \beta_6 g_a(k) + \ldots + \beta_{15} g_a(k-9) + \beta_{16} v(k) g_a(k) \end{aligned} \tag{5}$$

where β_0 to β_{16} are the parameters determined by least-square method for one type of vehicle, $T^{\mathrm{acc}}(k)$ and $T^{\mathrm{dec}}(k)$ are respectively the acceleration and deceleration duration since their inception up to the current time step k. At each time step, at least one of them is zero. To consider the grade angle α, the function g_a is defined as follows

$$g_a(k) = a(k) + g\left[\frac{\alpha(k)}{\sqrt{1+\alpha^2(k)}}\right] \tag{6}$$

POLY is an accurate emission model. However, it may underestimate emissions of higher emitting vehicles as it is built from average measured data (Qi et al., 2004).

While data-driven models can be developed quickly without prior knowledge on the vehicle or roads, they usually lack a clear physical interpretation and might be too coarse. They may also over-fit the calibration data if the number of variables considered is too large.

2.2. Physical modeling approach

An alternative method for estimating emissions and energy consumption is to employ a physical approach that leads to model parameters with physical meaning. Two types of models can be distinguished, the deterministic and probabilistic models, that are both described in the following sections.

2.2.1. Deterministic methods

The emission and energy consumption rates can be determined from the power engine demand P, which can be calculated using the following vehicle longitudinal dynamics, as in Sciarretta et al. (2015)

$$\begin{cases} Ma = F_{\mathrm{trac}} - F_{\mathrm{b}} - F_{\mathrm{res}} \\ a = \frac{dv}{dt} \end{cases} \tag{7}$$

where F_{trac} is the traction force transmitted by the powertrain to the wheels, F_{b} is the mechanical brake force and F_{res} is the resistance force that can be calculated as follows

$$F_{\mathrm{res}} = Mg\sin\alpha + MgC_{\mathrm{r}} + \frac{1}{2}dv^2AC_{\mathrm{a}} \tag{8}$$

The total tractive power of the vehicle is denoted P_{trac} and is given by

$$P_{\mathrm{trac}} = F_{\mathrm{trac}}v \tag{9}$$

(7) – (9) lead to

$$P_{\mathrm{trac}} = Mv\,(a + g\sin\alpha) + v\left(MgC_{\mathrm{r}} + \frac{d}{2}v^2AC_{\mathrm{a}}\right) + F_{\mathrm{b}}v \tag{10}$$

Finally, the power engine demand P can be calculated as follows

$$P = \frac{P_{\mathrm{trac}}}{\eta_{\mathrm{tf}}} + P_{\mathrm{acc}} \tag{11}$$

Once the power demand is known, Post et al. (1984) propose to estimate the emission and energy consumption rates as follows

$$J_y^{\mathrm{temp}} = \begin{cases} a_y + b_yP & \text{, if } P \geq 0 \\ a_y & \text{, if } P < 0 \end{cases} \tag{12}$$

a_y and b_y are the regression coefficients determined for a given y and vehicle type. When y represents the fuel consumption, a_y can be approximated by the following linear function

$$a_y = \gamma \times D \tag{13}$$

where γ is a constant.

Barth et al. (1996) propose to replace the regression coefficients by physical parameters and operation variables to approximate the fuel use rate. The model is defined as

$$J_{\mathrm{fuel}}^{\mathrm{temp}}LHV_{\mathrm{fuel}} \approx \lambda\left(C_{\mathrm{e}}nD + \frac{P}{\eta_{\mathrm{eng}}}\right) \tag{14}$$

where the engine friction factor C_{e} is the energy used at zero-power output to overcome engine friction.

An et al. (1997) then propose to calculate the pollutant emission rates as follows

$$J_y^{\mathrm{temp}} = J_{\mathrm{fuel}}^{\mathrm{temp}}\frac{dy}{d(\mathrm{fuel})}CPF_y \tag{15}$$

where y refers here only to emissions, $\frac{dy}{d(\mathrm{fuel})}$ corresponds to the grams of engine-out emissions per gram of fuel consumed for pollutant y, and the catalyst pass fraction CPF_y can be modeled as

$$CPF_y = 1 - \epsilon_y\exp\left[\left[-b - c\left(1 - \frac{1}{\lambda}\right)\right]J_{\mathrm{fuel}}^{\mathrm{temp}}\right] \tag{16}$$

The Comprehensive Modal Emissions Model (CMEM) is based on (15) (Scora and Barth, 2006). It considers different categories of vehicle and different modes of operation (idling, cruising, acceleration, and deceleration). Emission and fuel consumption rates are calculated as a function of the vehicle fleet composition (vehicle categorization based on model year, weight, etc.), operation variables and model-calibrated parameters. The structure of the model is shown in Fig. 3. The CMEM predicts emissions well, but may underestimate them for high-emitting vehicles because the model is based on the average data of 300 vehicles (including about 30 high emitters) measured during dynamometer tests, along different driving cycles (Rakha et al., 2003).

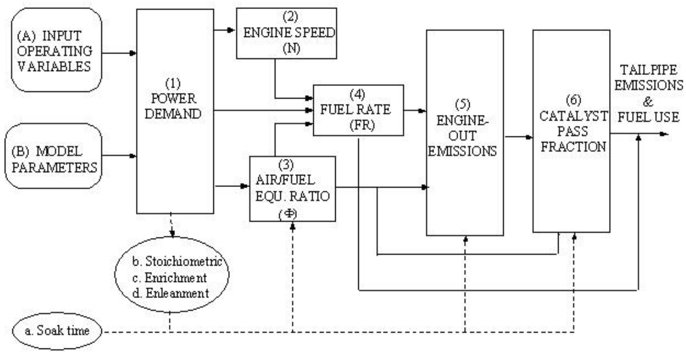

Figure 3: Structure of the CMEM (Scora and Barth, 2006) [Published with permission of the Center for Environmental Research and Technology].

Another model proposed by Gärtner et al. (2004) estimates emissions from fuel consumption at engine mechanics level. The model relies on the first Law of Thermodynamics and chemical kinetic reaction rate considerations. For NO_x emissions, the model reads

$$\log\left(\frac{d(\mathrm{NOx})}{d(\mathrm{fuel})}\right) = a_0 + a_1COC + a_2m_{\mathrm{cyl}} + a_3m_{O_2} \tag{17}$$

where $\frac{d(\text{NOx})}{d(\text{fuel})}$ is the mass of nitrogen oxides emitted per mass of fuel consumed, and $a_0 - a_3$ are model coefficients.

A simplified version of (17) is proposed by Thibault et al. (2016). The authors propose to express $\log(J_{\text{NOx}})$ as a linear function of the in-cylinder burnt gas ratio R_{BGR}, as follows

$$\log\left(\frac{d(\text{NOx})}{d(\text{fuel})}\right) = a_4 + a_5 R_{\text{BGR}} \tag{18}$$

where a_4, a_5 are model coefficients.

R_{BGR} is expressed as a function of the engine speed and the engine torque for a given type of vehicle, based on the data from the NEDC. The engine conditions are physically determined from the speed of the vehicle and its constant parameters.

The same approach can be considered to estimate the emissions of other pollutants.

2.2.2. *Probabilistic methods*

The previous models estimate emissions and energy consumption as a function of real vehicle operation variables (e.g. speed and acceleration, power demand, engine mechanics).

However, these data are not always available. One may obtain the velocity through microscopic traffic model simulation. But such models can be difficult to implement, especially on a large spatial scale with a lack of precise knowledge about the traffic situation, and can lead to unrealistically smooth velocity profiles. Hence, probabilistic models, based on random velocity disturbances, have been proposed in the literature.

The general idea of the random velocity disturbances approach is to run the emission and energy consumption models while replacing, for a given route, the actual speed of the vehicle by an approximate second-by-second speed profile built from a deterministic and a stochastic component as

$$\tilde{v} = \bar{v} + \Theta \tag{19}$$

where $\bar{v}$ is the average traffic speed estimated from the road attributes provided by a geographical information system (e.g. speed limit, traffic signs, road grade) and Θ is a random variation in velocity for the subject vehicle.

It is possible to consider a spatial distribution of speed or acceleration based on driving cycles or statistical distributions (Burghout, 2004).

Karbowski et al. (2014) combine Markov chains with deterministic route attributes to generate the speed profile. In this model, Θ is adjusted according to

$$P(X(k+1) = X_i | X(k) = X_j) = M_{\text{TP}}(i, j) \tag{20}$$

where $X(k) = [v(k)\ a(k)]^T$ is the state vector of the vehicle at time step k, and the transition probability matrix M_{TP} is built from real data.

Another probabilistic model is the Motor Vehicle Emission Simulator (MOVES), presented by Wu et al. (2014). The aim of this method is to make the velocity trajectory more realistic. Thus, it is assumed that vehicle detector stations provide an estimation of $\bar{v}$. The random variation in velocity is defined as

$$\Theta(k) = \tilde{v}(k-1) + a(k-1) - \bar{v}(k) \tag{21}$$

A procedure to determine the acceleration a is presented in Wu et al. (2014).

Probabilistic approaches are a solution in case of lack of information about the vehicle dynamics. By construction, they are less accurate than models based on the actual speed, but can be effectively used to estimate emissions and energy consumption (Kubička et al., 2016). To improve these methods, traffic prediction models could be integrated to determine $\bar{v}$ (cf. Section 3.1.2).

Note that the variability of certain unobserved parameters between vehicles (e.g. temperature, Reid vapor pressure) can affect the emissions and energy consumption. These issues can be addressed by introducing probabilistic correction factors (Frey and Zheng, 2002).

3. Emission and energy consumption models for traffic vehicular flows

The emission and energy consumption models presented in Section 2 are microscopic. They estimate emissions and energy consumption based on the instantaneous operating variables of individual vehicles, that can be obtained through microscopic traffic models. But on a network scale, they have the known disadvantage of high computational load, as their computation time increases sharply with the number of vehicles. The instantaneous operating variables can also be measured, but the data for so many vehicles are very difficult to obtain and process.

For large scale control purposes it is necessary to develop macroscopic models that use aggregate network or link-based data to estimate global emissions and energy consumption. These models are more coarse but also simpler to use and allow for faster computation. They are based on the traffic variables presented in Table 2.

In this section, we first review how to determine the traffic kinematics, then we present different emission and energy consumption models that can be set up.

3.1. *Traffic kinematics*

To determine the traffic kinematics, it is possible to measure the average speed of vehicles, or to use a traffic model based on fluid dynamics.

3.1.1. *Average speed*

The average speed of the traffic on each link i is defined as

$$\bar{v}(i) = \frac{1}{T}\sum_{k=1}^{T}\frac{1}{N(i,k)}\sum_{j=1}^{N(i,k)} v^j(k) \tag{22}$$

where T is the number of time steps on which the average speed is performed, $N(i,k)$ is the number of vehicles on link i at time step k and $v^j(k)$ denotes the speed of vehicle j at time step k. In the following, the average speed of link i, $\bar{v}(i)$, is referred to as $\bar{v}$ for simplicity.

The average speed can be provided using fixed sensors or Floating Car Data (FCD) methods, like the smartphone devices of the drivers for example. Similarly, the number of vehicles $N(i,k)$ can be provided by induction loops or cameras.

Symbol	Description
i	Cell index [–]
k	Discrete Time index [–]
L	Length of link [m]
$N_i(k)$	Number of vehicles in cell i at time step k [veh]
v	Traffic speed [m s^{-1}]
$\bar{v}$	Average traffic speed [m s^{-1}]
$v_{\max}$	Maximum speed, forward wave speed [m s^{-1}]
δ	Discrete-time step size [s]
δ_x	Discrete-space cell length [m]
ρ	Vehicle density [veh m^{-1}]
ρ^{cr}	Critical density, i.e. associated with the maximum flow [veh m^{-1}]
ρ^{M}	Maximum possible vehicle density [veh m^{-1}]
φ	Traffic flow [veh s^{-1}]
$\varphi_i(k)$	Traffic flow entering cell i during $[k\delta,\ (k+1)\delta]$ [veh s^{-1}]
φ^{M}	Maximum possible traffic flow [veh s^{-1}]
w	Backward wave speed [m.s^{-1}]

Table 2: Traffic variables and indices used in emission and energy consumption models.

3.1.2. Fluid-based models

The traffic kinematics can also be determined through dynamic fluid-based traffic models that describe the evolution of the traffic in the network as a fluid in a pipe. Some overviews presenting this kind of models can be found in Ferrara et al. (2018a,c); van Wageningen-Kessels et al. (2015); Hoogendoorn and Bovy (2001).

This approach provides the traffic variables, i.e. $\rho(x,t)$, $v(x,t)$, and $\varphi(x,t)$, at given position x and time t. It considers the traffic speed as a function of x and t. Therefore, unlike the average speed approach, these models reflect the speed differences along links and provide a dynamic traffic speed.

Some macroscopic traffic models are reviewed in the following. They are all based on the following conservation law

$$\frac{\partial}{\partial t}\rho(x,t) + \frac{\partial}{\partial x}(\rho(x,t)v(x,t)) = 0 \tag{23}$$

Some of these models are continuous and others are spatially and temporally discretized. A distinction is made between first and higher order models.

– First order models

• *Lighthill-Whitham-Richard model*

Lighthill and Whitham (1955) and Richards (1956) assume that v depends only on ρ. Hence, the flow can be expressed as a function of only ρ as

$$\varphi = \rho v(\rho) = \Phi(\rho) \tag{24}$$

The conservation law presented in (23) can then be expressed as

$$\frac{\partial}{\partial t}\rho + \frac{\partial}{\partial x}\Phi(\rho) = 0 \tag{25}$$

where Φ is a strictly concave C^1 function defined on $[0,\rho^{\mathrm{M}}]$ and satisfying $\Phi(0) = \Phi(\rho^{\mathrm{M}}) = 0$.

The relationship $\varphi = \Phi(\rho)$ is called the fundamental diagram. The most common fundamental diagrams are listed in Table 3 (Garavello et al., 2016), in which v_0 is a positive constant.

Fundamental Diagram	Expression
Greenshields et al. (1935)	$\Phi(\rho) = \rho v_{\max}\left(1 - \left(\frac{\rho}{\rho^{\mathrm{M}}}\right)^p\right),\ p \in \mathbb{N}$
Greenberg (1959)	$\Phi(\rho) = \rho v_0 \ln\left(\frac{\rho^{\mathrm{M}}}{\rho}\right)$
Underwood	$\Phi(\rho) = \rho v_{\max} \exp\left(-\frac{\rho}{\rho^{\mathrm{M}}}\right)$
California	$\Phi(\rho) = \rho v_0\left(\frac{1}{\rho} - \frac{1}{\rho^{\mathrm{M}}}\right)$
Trapezoidal (Daganzo, 1994)	$\Phi(\rho) = \min\left\{\rho v_{\max}, \varphi^{\mathrm{M}}, (\rho^{\mathrm{M}} - \rho)w\right\}$
Triangular (Newell, 1993)	$\Phi(\rho) = \min\left\{\rho v_{\max}, (\rho^{\mathrm{M}} - \rho)w\right\}$

Table 3: List of most common fundamental diagrams.

• *Cell transmission model*

Daganzo (1994) proposes the cell transmission model (CTM) which is a temporally and spatially discretized version of the LWR model based on the triangular or the trapezoidal fundamental diagram. The model is defined as

$$\begin{cases} \rho_i(k+1) = \rho_i(k) + \frac{\delta}{\delta_x}(\varphi_i(k) - \varphi_{i+1}(k)) \\ \varphi_i(k) = \min\left\{\rho_{i-1}(k)v_{\max},\ \varphi^{\mathrm{M}},\ w(\rho^{\mathrm{M}} - \rho_i(k))\right\} \end{cases} \tag{26}$$

• *Variable-length model*

In order to depict density evolution and track the congestion front, Canudas-de-Wit (2011) proposes the variable-length model (VLM) for highway traffic modeling. Illustrations are given on a closed ring road and on an urban road with traffic lights in Canudas-de-Wit and Ferrara (2018).

The VLM is also a discrete version of the LWR model based on the triangular fundamental diagram. The idea is to model any road section with only two lumped cells that are variable in length: an upstream cell in free flow and a downstream congested cell. Consider a road section of length L, then the length of the free and the congested cells will respectively be $L-l$ and l.

The main advantage of the VLM is that it is based on only three state variables: density in the upstream free cell ρ_{f}, density in the downstream congested cell ρ_{c}, and position of the congestion front l. The model reads

$$\begin{cases} \dot{\rho}_{\mathrm{f}} = [\varphi_{\mathrm{in}} - \varphi(\rho_{\mathrm{f}})]\frac{1}{L-l} \\ \dot{\rho}_{\mathrm{c}} = [\varphi(\rho_{\mathrm{c}}) - \varphi_{\mathrm{out}}]\frac{1}{l} \\ \dot{l} = \frac{\varphi(\rho_{\mathrm{f}}) - \varphi(\rho_{\mathrm{c}})}{\rho_{\mathrm{c}} - \rho_{\mathrm{f}}} \end{cases} \tag{27}$$

where the interface flows $\varphi(\rho_{\mathrm{f}})$ and $\varphi(\rho_{\mathrm{c}})$, which correspond to the demand of the free cell and the supply of the congested cell respectively, can be expressed as

$$\begin{aligned}\varphi(\rho_{\mathrm{f}}) &= \rho_{\mathrm{f}} v_{\max} \\ \varphi(\rho_{\mathrm{c}}) &= w(\rho^{\mathrm{M}} - \rho_{\mathrm{c}})\end{aligned} \tag{28}$$

φ_{in} and φ_{out} are the inflow and outflow at the boundaries of the section of length L. They are defined as

$$\begin{aligned}\varphi_{\mathrm{in}} &= \min\{D_{\mathrm{in}},\ s_{\mathrm{f}}\} \\ \varphi_{\mathrm{out}} &= \min\{D_c,\ S_{\mathrm{out}}\}\end{aligned} \tag{29}$$

where D_{in} and S_{out} are respectively the input demand and the output supply. D_c and s_{f} are

$$\begin{aligned}D_c &= \min\{\rho_{\mathrm{c}} v_{\max},\ v_{\max}\rho^{\mathrm{cr}}(v_{\max})\} \\ s_{\mathrm{f}} &= \min\left\{w(\rho^{\mathrm{M}} - \rho_{\mathrm{f}}),\ v_{\max}\rho^{\mathrm{cr}}(v_{\max})\right\}\end{aligned} \tag{30}$$

where $\rho^{\mathrm{cr}}(v_{\max})$ is the critical density relative to $v_{\max}$. It is defined as

$$\rho^{\mathrm{cr}}(v_{\max}) = \frac{w\rho^{\mathrm{M}}}{v_{\max} + w} \tag{31}$$

De Nunzio et al. (2014) propose to adapt the VLM to the urban environment by considering a binary variable ζ multiplying the boundary flows in (29) to model the behavior of traffic lights, as

$$\zeta = \begin{cases} 1 & \text{, if the traffic light is green} \\ 0 & \text{, else} \end{cases} \tag{32}$$

• *Link transmission model*

Yperman (2007) proposes the link transmission model (LTM), which is a discrete version of the LWR model based on the triangular fundamental diagram, with only one cell per road. Therefore, computation times are reduced.

The LTM introduces the notion of cumulative vehicle counts. $N_{\mathrm{up}}^{\mathrm{tot}}(k\delta)$ and $N_{\mathrm{down}}^{\mathrm{tot}}(k\delta)$ are respectively the cumulative entering and exiting vehicle count of a given link at $k\delta$, based on given split ratios at intersections.

The maximum number of vehicles that can be sent by this link to the next one during time interval $[k\delta,\ (k+1)\delta]$ is

$$S_{\mathrm{boundary}}(k) = N_{\mathrm{up}}^{\mathrm{tot}}\left((k+1)\delta - \frac{L}{v_{\max}}\right) - N_{\mathrm{down}}^{\mathrm{tot}}(k\delta) \tag{33}$$

The maximum number of vehicles that can leave the considered link during the time interval $[k\delta,\ (k+1)\delta]$ is

$$S_{\mathrm{link}}(k) = \rho^{\mathrm{M}} L\delta \tag{34}$$

The number of vehicles sent by the link to the next one is then simply

$$S(k) = \min\left\{S_{\mathrm{boundary}}(k),\ S_{\mathrm{link}}(k)\right\} \tag{35}$$

In the same way, the number of vehicles $R(k)$ received by the link is expressed as

$$\begin{cases} R(k) = \min\left\{R_{\mathrm{boundary}}(k),\ R_{\mathrm{link}}(k)\right\} \\ R_{\mathrm{boundary}}(k) = N_{\mathrm{down}}^{\mathrm{tot}}\left((k+1)\delta - \frac{L}{w}\right) + \rho^{\mathrm{M}} L - N_{\mathrm{up}}^{\mathrm{tot}}(k\delta) \\ R_{\mathrm{link}}(k) = \rho^{\mathrm{M}} L\delta \end{cases} \tag{36}$$

• *Queue models*

Queue models are interested in the length of the queues at the end of each link i. An example is the Berg-Lin-Xi (BLX) model, presented by Van den Berg et al. (2007) and Lin and Xi (2008). Lin et al. (2012) propose an extension of the BLX model. Like the LTM, the BLX model considers flows between the links.

The queue on link i is composed of N_i^q vehicles. When the traffic light is green, the number of vehicles entering cell i from the upstream cell during time interval $[k\delta,\ (k+1)\delta]$ is

$$\delta\varphi_i(k) = \max\left\{0,\ \min\left\{N_{i-1}^q(k) + \delta\varphi_{i-1}(k), S_i(k), \delta\varphi^{\mathrm{M}}\right\}\right\} \tag{37}$$

where $S_i(k)$ denotes the available storage of link i at time step k, expressed in number of vehicles.

The queue length and the available storage can be expressed as

$$\begin{cases} N_i^q(k+1) = N_i^q(k) + \delta(\varphi_i(k) - \varphi_{i+1}(k)) \\ S_i(k+1) = S_i(k) + \delta(\varphi_{i+1}(k) - \varphi_i(k)) \end{cases} \tag{38}$$

The total number of vehicles in link i at time step k can be determined as

$$N_i(k) = \rho^{\mathrm{M}} L - S_i(k) \tag{39}$$

• *Summary*

The LWR model and its discrete variations, presented above, are simple first order mathematical representations of the traffic inspired by fluid mechanics. They are based on fundamental diagrams that associate φ to ρ. These models are able to capture realistic traffic phenomena such as shock waves, physical queues and queue spillbacks (Garavello et al., 2016).

However, first-order models based on the fundamental diagram are not sufficient to capture unstable traffic variations caused by the inertia of vehicles because they assume that v is always in equilibrium. Consequently, they have limitations in capturing complex traffic phenomena such as stop-and-go waves, capacity drops and phantom jams (formation of clusters of cars with high densities due to the driving style of road users Kerner and Konhäuser (1993)). These must be taken into account in order to best estimate emissions and energy consumption.

– *Second order models*

Second order models have been developed in order to capture more realistic traffic behavior in congested areas. They still consider the equation for the conservation of vehicles presented in (23) and use the fundamental diagram to determine the steady state of the system, but they have an additional equation for the conservation of momentum.

- *Payne-Whitham model*

An example of a well known second order model is proposed in Payne (1971). The model has the following form

$$\begin{cases} \partial_t \rho + \partial_x(\rho v) = 0 \\ \partial_t v + v\partial_x v + \frac{1}{\rho}\partial_x(p(\rho)) = \frac{1}{\tau}(v_e(\rho) - v) \end{cases} \tag{40}$$

where $v_e(\rho)$ is the equilibrium speed given by the fundamental diagram, and $p(\rho)$ is analogous to the pressure in the fluid dynamics equations and depends on the density (Piccoli and Tosin, 2009).

The anticipation term $\frac{1}{\rho}\partial_x(p(\rho))$ models the reaction of vehicles, i.e. acceleration or deceleration, to the variations of ρ. The relaxation term $\frac{1}{\tau}(v_e(\rho) - v)$ models the tendency of vehicles to travel from v towards $v_e(\rho)$ within a time $\tau > 0$ that represents the time needed by the vehicles to adjust their actual speed to $v_e(\rho)$.

The second equation of (40) is the acceleration equation. Whitham (1974) proposes to simplify the model by considering $p(\rho)$ as a constant. Other expressions for this term exist, they are presented in Garavello et al. (2016), as well as the modeling of an additional viscous term in this equation.

- *Aw-Rascle-Zhang model*

Daganzo (1995) highlights some limitations of the Payne-Whitham model presented above. In particular, the model allows the vehicles to travel with negative speed.

To tackle this problem, Aw and Rascle (2000) and Zhang (2002) propose the following model

$$\begin{cases} \partial_t \rho + \partial_x(\rho v) = 0 \\ \partial_t(v + p(\rho)) + v\partial_x(v + p(\rho)) = 0 \end{cases} \tag{41}$$

where the pressure term p may be defined as

$$p(\rho) = \rho^{\gamma}, \quad \gamma > 0 \tag{42}$$

- *METANET model*

Messmer and Papageorgiou (1990) present the METANET model which is a discrete version of the Payne-Whitham model presented in (40). It reads

$$\begin{cases} \rho_i(k+1) = & \rho_i(k) + \frac{\delta}{\delta_x}(\varphi_i(k) - \varphi_{i+1}(k)) \\ v_i(k+1) = & v_i(k) + \frac{\delta}{\gamma_1}[v_e(\rho_i(k)) - v_i(k)] \\ & + \frac{\delta}{\delta_x} v_i(k)[v_{i-1}(k) - v_i(k)] - \frac{\gamma_2 \delta[\rho_{i+1}(k) - \rho_i(k)]}{\gamma_1 \delta_x[\rho_i(k) + \gamma_3]} \end{cases} \tag{43}$$

and the authors propose the following fundamental diagram to define the equilibrium speed $v_e(\rho)$

$$v_e(\rho_i) = v_{\max} \exp\left[-\frac{1}{\gamma_4}\left(\frac{\rho_i(k)}{\rho^{\mathrm{cr}}}\right)^{\gamma_4}\right] \tag{44}$$

where $\gamma_1 - \gamma_4$ are model coefficients.

METANET was originally introduced to capture traffic phenomena on highways. The proceeding of flows between the segments is fully presented in Messmer and Papageorgiou (1990).

– *Phase transition and higher order models*

Second order models generally have higher computation times. Phase transition models are a good alternative to the extent that they behave like the classic LWR model when the traffic is free and like a second-order model when the traffic is congested. This allows to capture complex traffic phenomena while keeping reasonable computation times for free-flow traffic.

Colombo (2002) proposes the following phase transition model

- For free flow traffic, the author considers the LWR model, presented in (25), with the Greenshields fundamental diagram (cf. Table 3, with $p = 1$).
- For congested traffic, v cannot be considered as a function only of the density anymore. In this case, the density-flow points are scattered in a two-dimensional region, based on the following second-order model

$$\begin{cases} \partial_t \rho + \partial_x(\rho v) = 0 \\ \partial_t q + \partial_x((q - Q)v) = 0 \end{cases} \tag{45}$$

where q is the momentum, Q is a parameter of the road considered, and v is expressed as

$$v = \left(1 - \frac{\rho}{\rho^{\mathrm{M}}}\right)\frac{q}{\rho} \tag{46}$$

The associated hybrid fundamental diagram is shown in Fig. 4.

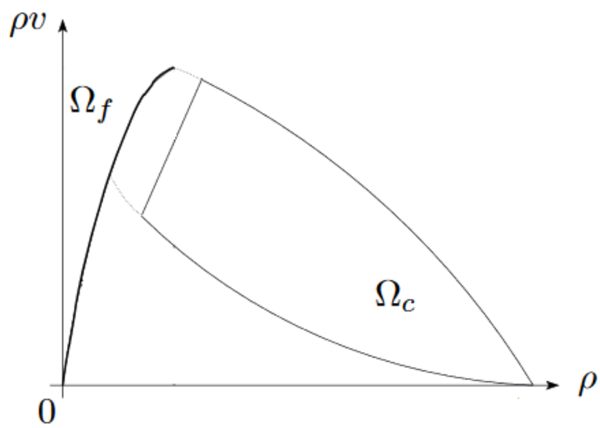

Figure 4: Fundamental diagram of the phase transition model, representing the free region Ω_f and the congested region Ω_c (Colombo, 2002) [Copyright ©2002 Society for Industrial and Applied Mathematics. Reprinted with permission. All rights reserved].

Finally, higher-order models exist but they are less appropriate for emissions and energy consumption estimation as their computation times are higher. An example of third order model, where the additional equation is for the variance of the speed, can be found in Helbing (1995). This method is useful to describe the increase of the speed variance just before traffic jams occur.

– Network-wide extension

The traffic models presented above can be extended across a network. The junctions represent a very important part of the extended model. Basically, each junction can be reduced to a combination of simple merge and diverge junctions (Garavello et al., 2016). A complete overview of macroscopic node models can be found in Tampère et al. (2011). The authors present macroscopic node model instances both for signalized and unsignalized intersections.

In the case of the extended CTM, a fundamental diagram is associated with each link, each link being partitioned into uniform cells. An urban version of the CTM is proposed in Xie et al. (2013). The authors use turning ratios assigned to intersections and distinguish two possibilities. First, a cell preceding an intersection can be composed of one traffic light. Such cells have one unique queue, and all the vehicles merge into it. Second, the cell can be divided into sub cells so that each direction has its own traffic light.

Similarly, the LTM can be extended considering the flows sent and received by links (Garavello et al., 2016). Regarding queue models, Lin et al. (2012) consider the case of links with multiple junctions (connected to several upstream and downstream links) and, for control purposes, present the S model, which is basically a simplification of the BLX model, with a time interval equal to the traffic-light cycle.

The network-wide extension approach is similar for second order traffic models. For example, Garavello et al. (2016) present the extension of the Aw-Rascle-Zhang model on a network scale. A more detailed description of this model at junctions can be found in Herty and Rascle (2006).

For control purposes, De Nunzio et al. (2014) suggest to simplify the VLM by assuming an average continuous flow through the traffic lights by replacing the binary variable ζ with $\frac{T_{\text{green}}}{T_{\text{cycle}}}$, where T_{green} and T_{cycle} denote respectively the green phase time and the cycle time of the traffic light. This method is inspired by store-and-forward models, originally suggested by Gazis and Potts (1963). It allows to describe the urban traffic without using binary variables. Hence, polynomial complexity control methods can be applied to the system, which allows for consideration of large-scale networks. However, due to this simplification, the effect of offsets between traffic lights of successive intersections is not depicted. Moreover, the oscillations of the system (stop-and-go waves, propagation waves, etc.) are not represented, which is a crucial point for emissions and energy consumption estimation (Hall, 2012; Aboudolas et al., 2009).

3.2. Emission and energy consumption meta-models

In Section 3.1, we reviewed some methods to determine the traffic kinematics, either by measuring the static average speed (cf. Section 3.1.1), or by using dynamic fluid-based traffic models (cf. Section 3.1.2). In this section, we present the meta-models used to calculate emissions and energy consumption from the traffic dynamics, considering either approach.

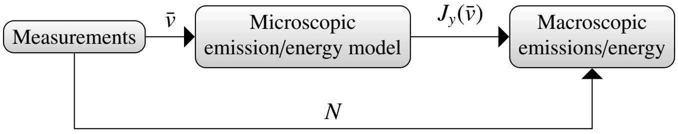

Figure 5: Structure of the emission and energy consumption meta-model associated with static average speed-based approaches.

3.2.1. Meta-model associated with static average speed-based approaches

Emissions and energy consumption can be calculated by considering an average speed-based approach. This is done by a meta-model whose general procedure is illustrated in Fig. 5, and operation steps are presented below.

1. The average speed $\bar{v}$ and the number of vehicles N are measured, or estimated.
2. The emission or energy consumption rate of a single vehicle J_y is calculated from $\bar{v}$ using a microscopic emission and energy consumption model (cf. Section 2).
3. $J_y(\bar{v})$ is then multiplied by N to approximate the total emission or energy consumption rate.

Note that this procedure can be conducted at different scales. The average speed $\bar{v}$ and the number of vehicles associated N can refer to a single link of a network, if the data are available, or to a larger spatial area. Moreover, the duration between two successive measurements usually depend on the measuring devices. These issues are addressed in Section 3.3.

This meta-model can be associated either with a data-based or a physical microscopic emission and energy consumption model. These approaches are detailed below. Note that they involve measuring, or estimating, the number of vehicles on the roads under consideration.

• Data-based model

Some authors propose to associate the meta-model with a data-based microscopic emission and energy consumption model.

For instance, Boriboonsomsin et al. (2012) propose the following regression-based model in order to estimate the fuel use rate of a single vehicle

$$\ln\left(J_{\text{fuel}}^{\text{spat}}\right) = \beta_0 + \beta_1\bar{v} + \beta_2\bar{v}^2 + \beta_3\bar{v}^3 + \beta_4\bar{v}^4 + \beta_5\alpha \tag{47}$$

where β_0 to β_5 are the regression coefficients.

Another common approach to estimate emissions and energy consumption on a large spatial scale is to associate this meta-model with a microscopic model based on aggregated data-driven emission or energy consumption factors $J_y(\bar{v}, \theta)$ that depend on the traffic average speed $\bar{v}$ and some vehicle parameters θ.

Let Ω be the set of possible parameters sets. Aggregated factors are usually simply the mean values of experimental measurements and are typically expressed in mass of pollutant emitted (or mass of fuel consumed) per vehicle and per unit distance traveled. Hence, the total emission or energy consumption rate (per distance traveled), i.e. the output of the meta-model, of a link i containing $N(i, \theta)$ vehicles with the set of parameters θ is given by

$$J_y^i = \sum_{\theta \in \Omega} N(l, \theta) J_y(\bar{v}, \theta) \tag{48}$$

In practice, detailed information on the fleet composition is not available. Hence, a reference set can be considered, i.e. all the vehicles have the same parameters $\bar{\theta}$, and the emission or energy consumption rate on link i simply becomes:

$$J_y^i = N(i, \bar{\theta}) J_y(\bar{v}, \bar{\theta}) \tag{49}$$

The COPERT (COmputer Programme to calculate Emissions from Road Transport) model (Ntziachristos et al., 2009) developed by the European Environment Agency is based on this method. Several vehicle parameters are included in θ: the vehicle type (passenger car, light commercial vehicle, heavy duty vehicle, L-category vehicle), the fuel type, the engine displacement and its registration date. The sets of parameters of all the vehicles constitute the vehicle fleet composition. An example of emission factors obtained with COPERT for different types of vehicle as a function of the speed is given in Fig. 6.

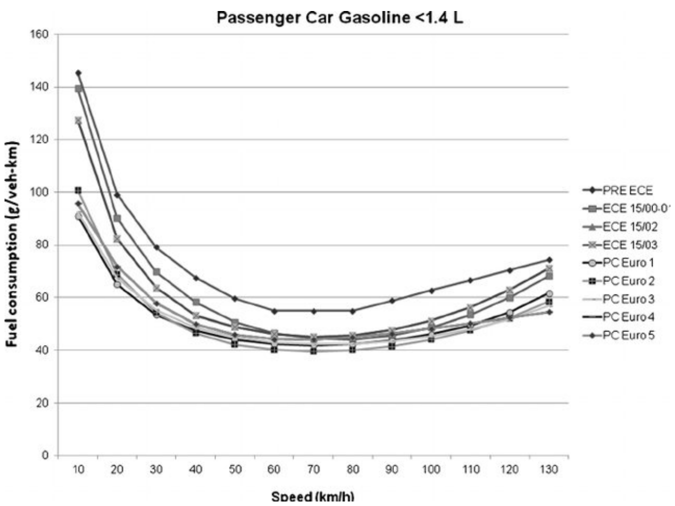

Figure 6: Fuel consumption factors of different gasoline passenger cars calculated with COPERT (Sobrino et al., 2014) [Published with permission of Networks and Spatial Economics].

Hausberger (2009) proposes the HBEFA (HandBook Emission FActors for road transport) model, which is more precise. This method additionally considers the driving conditions (highways, urban roads, stop-and-go traffic) and the volume-to-capacity ratio (number of vehicles divided by the capacity of the link), which is a dynamic variable, to determine $J_y(\bar{v}, \theta)$.

The accuracy can also be improved by multiplying the emission and energy consumption factor $J_y(\bar{v}, \theta)$ by a congestion correction factor, as does the TEE (Traffic Energy and Emissions) model. The objective is to represent the effect of congestion on emissions and energy consumption. The congestion correction factor depends on the average speed, the traffic-light timing, the link length, and the traffic density (Negrenti, 1999). These variables and parameters are used to estimate the time spent in each traffic situation (cruising, acceleration, deceleration and idling) and thus reflect the speed variability along the considered road link. The corresponding speed profile can then be reconstructed.

One limitation of these aggregated factors models is that the emission and energy consumption factors are not fundamental, as they depend on the driving cycle used during the measurements.

- *Physical model*

It is also possible to use this meta-model by associating it with a physical emission and energy consumption model.

For example, Jurik et al. (2014) propose to use the following microscopic physical model to estimate the energy consumption of a vehicle on link i

$$E_y(i) = J_y^i L(i) = \begin{cases} E^{\mathrm{r}}(i) + (\nu - 1) E^{\mathrm{p}}(i) & , \text{if } E^{\mathrm{p}}(i) \leq 0 \\ E^{\mathrm{r}}(i) & , \text{if } E^{\mathrm{p}}(i) > 0 \end{cases} \tag{50}$$

where $L(i)$ is the length of the link i, and $\nu \in [0, 1]$ is the downhill potential energy recuperation coefficient. The resistance and the potential energies are respectively given by

$$\begin{aligned} E^{\mathrm{r}}(i) &= \frac{d}{2} A C_{\mathrm{d}} \bar{v}^2 L(i) + M g C_{\mathrm{r}} L(i) \cos\alpha \\ E^{\mathrm{p}}(i) &= M g L(i) \sin\alpha \end{aligned} \tag{51}$$

To model more precisely the speed change at an intersection, De Nunzio et al. (2017) introduce a transition speed at the interface between two links of respective average speeds $\bar{v}_{\text{before}}$ and $\bar{v}_{\text{after}}$ defined as

$$v_{\text{transition}} = \beta \frac{\bar{v}_{\text{before}} + \bar{v}_{\text{after}}}{2} \tag{52}$$

where $\beta \in [0, 1]$ is a parameter depending on the type of interface (e.g. stop sign, traffic light, turning movement, etc.). This transition speed can be introduced to any model similar to the one presented in (50) – (51) to better model intersections.

3.2.2. *Meta-model associated with dynamic fluid-based models*

Emissions and energy consumption can be calculated by considering the fluid-based models dynamics. This is done by another meta-model whose general procedure is illustrated in Fig. 7, and operation steps are presented below.

1. First, a dynamic fluid-based traffic model is chosen (cf. Section 3.1.2). It provides the traffic variables, i.e. $\rho(x, t)$, $v(x, t)$, $\varphi(x, t)$.
2. Then, these variables are processed by an interface to generate groups of vehicles $g(x, t)$ sharing the same speed and acceleration. The interface calculates the speed, acceleration and number of vehicles of each group. They are respectively denoted $v(g(x, t))$, $a(g(x, t))$ and $N(g(x, t))$.

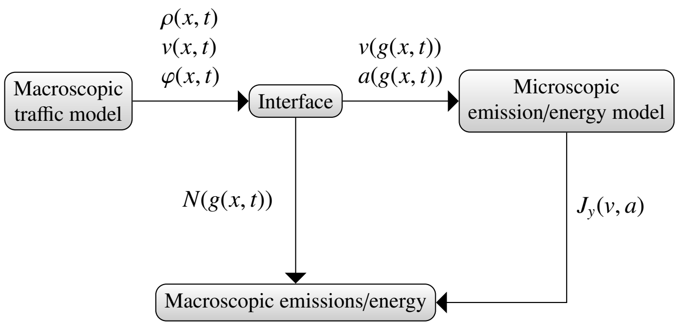

Figure 7: Structure of the emission and energy consumption meta-model associated with dynamic fluid-based traffic models.

3. A microscopic emission and energy consumption model is chosen (cf. Section 2). It provides the emission or energy consumption rate $J_y(v,a)$ of a vehicle of group $g(x,t)$ using the outputs $v(g(x,t))$ and $a(g(x,t))$ of the interface.
4. The emission or energy consumption rate $J_y(v,a)$ of a vehicle of group $g(x,t)$ is multiplied by the number of vehicles in the corresponding group $N(g(x,t))$ to provide the total emission or energy consumption rate of group $g(x,t)$.

The procedure presented above is repeated as many times as there are groups. It is important to note that this generation of groups with homogeneous operation variables relies on the spatial and temporal discretizations of the traffic model. This issue is addressed in Section 3.3.

The procedure of the interface presented above is detailed in the following (Zegeye et al., 2013).

To compute emissions and energy consumption, the employed traffic models are often discrete both in time and in space. Hence, two acceleration components have to be considered: the temporal and the spatial accelerations:

- The temporal acceleration describes the change in speed of vehicles within a cell from one time step to the next. It only applies to the vehicles that remain in the cell. It is expressed as

$$a_i^{\text{temp}}(k) = \frac{v_i(k+1) - v_i(k)}{\delta} \tag{53}$$

The number of vehicles subject to this acceleration, i.e. that stay within the cell i from time step k to time step $k+1$ is equal to

$$N_i^{\text{temp}}(k) = \delta_x \rho_i(k) - \varphi_i^{out}(k)\delta \tag{54}$$

where $\varphi_i^{out}(k)$ is the outflow of cell i during time interval $[k\delta,\ (k+1)\delta]$. The first term represents the number of vehicles initially in cell i at time step k.

These vehicles constitute a group $g(x,t)$ mentioned above. There are as many groups of this type as there are cells in the spatial discretization of the traffic model.

- The spatial acceleration describes the change in speed of vehicles moving from cell i to cell j. It is defined as

$$a_{i,j}^{\text{spat}}(k) = \frac{v_j(k+1) - v_i(k)}{\delta} \tag{55}$$

The number of vehicles subject to this acceleration, i.e. that move from the cell i to cell j during time interval $[k\delta,\ (k+1)\delta]$ is

$$N_{i,j}^{\text{spat}}(k) = \varphi_{i,j}(k)\delta \tag{56}$$

where $\varphi_{i,j}(k)$ is the flow of vehicles moving from cell i to cell j.

These vehicles constitute a group $g(x,t)$ mentioned above. There are as many groups of this type as there are cells interfaces in the spatial discretization of the traffic model.

Ultimately, a generic formulation to calculate the emissions and energy consumption rate in a network made of n cells is

$$J_y^{\text{network}}(k) = \begin{array}{l} \sum_{i=1}^{n} J_y(a_i^{\text{temp}}(k), v_i(k)) N_i^{\text{temp}}(k) + \\ \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{i,j} J_y(a_{i,j}^{\text{spat}}(k), v_i(k)) N_{i,j}^{\text{spat}}(k) \end{array} \tag{57}$$

where $\alpha_{i,j}$ is a binary variable equal to 1 if cells i and j are connected in the sense that vehicles can move directly from cell i to cell j, $\alpha_{i,j}$ equals zero otherwise. The first term of (57) refers to the emissions and energy consumption of vehicles staying in the same cell from time step k to $k+1$, and the second term refers to those of vehicles moving from one cell to another.

To estimate emissions and energy consumption more precisely, this calculation can be done by differentiating classes of vehicles. In that case, the function J_y can consider the real parameters of the vehicles instead of average values.

This meta-model can be associated either with a data-based or a physical microscopic emission and energy consumption model. Some examples are presented below. Naturally, the meta-model procedure is generic and can be adopted to other models.

- *Data-based model*

Some authors propose to use this meta-model by associating it with a data-based emission and energy consumption model. For example, Zegeye et al. (2013) propose to integrate the macroscopic traffic second order model METANET with the microscopic data-driven emission and fuel consumption model VT-micro. The resulting meta-model, called VT-macro, is mainly suitable for modeling emissions and energy consumption on highways.

Similarly, Lin et al. (2013) suggest to associate the traffic first order S model with VT-micro in an urban network. The authors present a set of possible behaviors for the vehicles (e.g. free, idling, accelerating, decelerating, start-and-stop behavior). Another use of the meta-model in an urban environment can be found in Jamshidnejad et al. (2017), in which the authors propose the same models association.

• *Physical model*

It is also possible to use this meta-model by associating it with a physical emission and energy consumption model. For example, De Nunzio et al. (2014) develop a method based on the VLM and a physical approach to determine energy consumption. This model considers only the spatial component of acceleration. In each cell, energy consumption is determined from the cell average speed (either free or congested), considering zero temporal acceleration. At the interface of the cells, the energy is calculated based on the following spatial acceleration

$$a_{i,j}^{\text{spat}} = \min\left\{a_{\max}, \frac{v_j - v_i}{\delta}\right\} \tag{58}$$

where the maximum acceleration $a_{\max}$ is a model parameter. Note that time does not appear in the formulation of De Nunzio et al. (2014) because the analysis is performed at steady state.

3.3. Spatial and temporal discretizations

The spatial and temporal discretizations of the methods used are a crucial point in emissions and energy consumption estimation: a compromise has to be found between precision and computation time.

• *Spatial discretization*

Concerning the use of the average speed meta-model, measurements of average speed and number of vehicles made on a road level would naturally give better results than measurements made on a larger spatial scale. But this depends mainly on the devices used to monitor the traffic. Some average speed-based meta-models consider a fine spatial discretization in order to be compatible with urban networks (e.g. COPERT Street Level (Rai et al., 2017)).

When using the meta-model associated with dynamic fluid-based models, the choice of the spatial discretization step size should be given some thought. A balance concerning the number of cells and their length has to be found in order to satisfy the desired accuracy without excessively increasing computation times.

• *Temporal discretization*

Some authors have proposed methods to use the average speed meta-model with high-frequency data inputs, i.e. average speeds and number of vehicles updated at high frequency. For example, Lejri et al. (2018) propose a method to adapt the COPERT emission and fuel consumption model to high-frequency data inputs. This kind of approach is more precise. However, it is essential to note that the average speed-based meta-model is static. In other words, even with high frequency data inputs, emissions and energy consumption are calculated for successive average speeds, but do not consider the acceleration of vehicles, yet crucial to fully characterize emissions and energy consumption (Ahn and Rakha, 2008).

The dynamic fluid-based meta-model considers vehicles accelerations. Therefore, this approach is more precise, but its crucial point is the estimation of the acceleration. In the formulation proposed in Section 3.2.2, the choice of δ must lead to realistic accelerations values while respecting the Courant–Friedrichs–Lewy (CFL) condition expressed as

$$2\delta v_{\max} \leq \delta_x \tag{59}$$

• *Summary*

In other words, adopting a dynamic fluid-based approach with very long time step size and length of cells is similar to having an average speed-based approach. The difference would be that the data are obtained by simulation instead of being measured.

Finally, the most precise way to calculate emissions and energy consumption at a large spatial scale would be to use a microscopic traffic model and to associate it with a microscopic emission and energy consumption model (cf. Section 2). In fact, this approach is the only one able to reflect differences in microscopic drivers' behavior (e.g. sudden deceleration, merging, lane changing). When traffic is congested, these can result in shock waves causing traffic breakdown, that a macroscopic traffic model cannot depict (Khondaker and Kattan, 2015b). However, this method is not possible at large scale because of the enormous computation times generated by the large number of vehicles considered. Schiper (2017) proposes a statistical approach to process this large amount of data by introducing sampling methods. The author suggests to estimate emissions and energy consumption only in some relevant locations of the network, and to extend the estimations at larger scales.

4. Single vehicles control design for emission and energy consumption reduction

In Sections 2 and 3, emission and energy consumption models have been presented for single vehicles and for traffic flows. In this section, we review some control strategies for single vehicles aiming at limiting emissions and energy consumption. They can be mostly categorized into eco-driving, i.e. computing a vehicle speed trajectory that minimizes the emissions or energy consumption along a given route, and eco-routing, i.e. planning a minimum energy or emissions route. An excellent overview of the existing vehicle control strategies is given by Guanetti et al. (2018).

4.1. Eco-driving

Eco-driving consists in computing a vehicle trajectory that minimizes the emissions or energy consumption along a given route, under technical (speed, acceleration and brake characteristics of the vehicle) and environment (traffic, traffic signs, traffic lights, etc.) constraints (Guanetti et al., 2018).

We define the state vector of a vehicle at time step k as $x(k) = [s(k), \ v(k)]^T$, where s and v respectively denote the vehicle's position along the route and the speed of the vehicle. Let F_{trac} and F_{b} be respectively the traction force at the wheels and the mechanical brake force, the objective of the eco-driving algorithm is to find at each time step k the input vector $u(k) = [F_{\text{trac}}(k), \ F_{\text{b}}(k)]^T$ that minimizes the emissions or the energy consumption calculated by the function g. The objective function g is similar to those presented in Section 2. It may consider vehicle parameters like its mass and parameters of the environment like the road slope, usually provided by a Geographic Information System (GIS).

Sciarretta et al. (2015) formulate the eco-driving optimization problem as follows

$$\underset{u_0,\ldots,u_{n-1}}{\text{minimize}} \quad \sum_{k=0}^{n-1} g(x(k), u(k)) \tag{60}$$

subject to

$$\left.\begin{array}{l} x(k+1) = f(x(k), u(k)), \\ 0 \leq s(k) \leq s_{\mathrm{f}}, \\ v_{\min}(k, s(k)) \leq v(k) \leq v_{\max}(k, s(k)), \\ F_{\mathrm{trac,min}}(v(k)) \leq F_{\mathrm{trac}}(k) \leq F_{\mathrm{trac,max}}(v(k)), \\ F_{\mathrm{b,min}} \leq F_b(k) \leq F_{\mathrm{b,max}}, \end{array}\right\} \forall k \in [0\,..\,n-1]$$
$$x(0) = x_0,$$
$$x(n) = x_{\mathrm{f}}. \tag{61}$$

The state of the vehicle at time step $k+1$ is given by the following function based on the vehicle dynamics

$$f(x(k), u(k)) = \begin{pmatrix} s(k) + \delta v(k) \\ v(k) + \frac{\delta}{M}(F_{\mathrm{trac}}(k) - F_{\mathrm{b}}(k) - F_{\mathrm{res}}(k)) \end{pmatrix} \tag{62}$$

where F_{res} is the resistance force, expressed in (8). The technical limits of the vehicle consist in bounding the input variables F_{trac} and F_{b} as indicated in (61). The function $v_{\min}$ and $v_{\max}$ define a convex constraint set that takes into account the environment constraints associated with speed limits, traffic lights, traffic signs, road curvature, etc. $x_0 = [s_0,\ v_0]^T$ and $x_{\mathrm{f}} = [s_{\mathrm{f}},\ v_{\mathrm{f}}]^T$ are the initial and final constraints of the eco-driving problem.

The eco-driving problem considering F_{trac} and F_{b} as control inputs is perfectly compatible with autonomous vehicles, which include the control in the longitudinal and lateral directions, as it gives instructions to the powertrain. However, it is expected from an eco-driving problem for human drivers to return an advisory speed profile the user can follow. In that case, the algorithm may return at each time step k the speed instruction $v(k+1)$ calculated with (62) instead of $F_{\mathrm{trac}}(k)$ and $F_{\mathrm{b}}(k)$. Another solution is to directly formulate the optimization problem considering the recommended maximal speed of the vehicle as the control input (Ozatay et al., 2014a; Boehme et al., 2013).

Sciarretta et al. (2015) present several algorithms aiming at solving the eco-driving problem given in (60) – (62). These solutions can either be offline, i.e. consider all road characteristics known in advance, or online, i.e. make use of real-time estimations on a vehicle immersed in its environment.

Many solutions can be used for offline optimization: dynamic programming (Dib et al., 2012), Pontryagin's minimum principle (Sciarretta et al., 2015) or calculating the analytical solution (Ozatay et al., 2014b).

Online solutions allow to acquire more information in real time about the upcoming route. For example, Hellström et al. (2009) propose a method with an on board optimizing controller taking into account the road slope. In the case of connected vehicles, one may also imagine a control design taking into account the prediction of the upcoming traffic conditions and accordingly updating the $v_{\min}$ and $v_{\max}$ constraints of (61). The main limitation of these online solutions is the computation time as they are expected to be compatible with real-time execution.

In an urban environment, eco-driving is complex because of the uncertainty of traffic. In particular, it is very difficult to know the traffic-light cycles in advance as some signalized intersections have a variable phase duration depending on the traffic level. Intelligent transportation systems and traffic infrastructure connectivity are expected to reduce this uncertainty (Dimitrakopoulos and Demestichas, 2010).

If the traffic-light cycles are unknown by the eco-driving algorithm, Ozatay et al. (2014a) propose a method that considers traffic lights as stop signs in the optimization problem. Naturally, the driver is free not to follow the advised velocity given by the algorithm in the case of green at a traffic light.

To take into account the uncertainty about traffic-light cycles, Sun et al. (2018) consider a stochastic cycle timing that adds to the red-light duration a random variable. To generate more realistic signal timings, Mahler and Vahidi (2012) introduce for each intersection a time-varying probability of green based on measured data. In the optimization process, solutions that pass through time intervals with high green probability are then naturally preferred.

In the case of known and deterministic traffic-light cycles, many algorithms can be used to solve the eco-driving problem. For example, Miyatake et al. (2011) present a method based on dynamic programming, De Nunzio et al. (2016) use Dijkstra's shortest path algorithm, HomChaudhuri et al. (2017) develop a method with model predictive control, and Seredynski et al. (2013) implement a genetic algorithm. The principle of these algorithms is to add a constraint on the crossing time at intersections.

To improve the safety and avoid rear-end collisions, Zhang and Cassandras (2018) propose a control strategy for vehicles crossing an urban signal-free intersection. The principle is to generate acceleration profiles for the vehicles in order to cross the merging zone in a limited time while minimizing the acceleration. This approach is adapted for autonomous vehicles, but the authors consider a mixed traffic in their simulation (autonomous and human-piloted vehicles) and analyze the impact of the proportion of autonomous vehicles on their acceleration. Human-piloted vehicles are subject to priority rules.

Eco-driving algorithms need information about the traffic situation in order to be accurate. These data can be provided either by sensors or by a macroscopic traffic model. Many parameters of the problem, like pedestrians or drivers decision making, remain uncertain and unpredictable.

Autonomous vehicles raise the issue of their safety, but they offer prospects in terms of energy savings as they can accurately track the instructions generated by the eco-driving algorithm (Han et al., 2018). Moreover, if the autonomous vehicles communicate with each other, they can reduce their energy consumption by coordinating and forming micro-platoons along the route, even if they have different origins and destinations (Lelouvier et al., 2017).

4.2. *Eco-routing*

Eco-routing consists in planning an emission or energy-minimal route, given an origin and a destination. The function that attributes to each link the energy consumption (or the emissions) of a vehicle traveling along this link is denoted g.

In the case of static eco-routing algorithms, the function g depends only on the link under consideration. In the general case, the function g depends on the time t as the traffic situation in the network evolves over time.

Ericsson et al. (2006) present an eco-routing algorithm that classifies the roads of the network into 6 groups, depending on their GPS data. Based on the same data, a fuel consumption factor is calculated for each group. Then, the function g assigns to each link its energy consumption, using the fuel consumption factor and the length of the link. The authors introduce peak and off-peak hours to model the evolution of the traffic during the day. Similarly, Boriboonsomsin et al. (2012) propose to consider not only historical GPS data, but also real-time vehicle velocity trajectories to estimate the energy consumption of each link, i.e. build the function g.

Usually, eco-routing algorithms only take into account the energetic cost of links and not the vehicle behavior at intersections. However, this aspect is crucial in energy consumption estimation. To model the energy consumption at intersections, De Nunzio et al. (2017) introduce a transition speed at the interface between two links, given in (52). Traffic lights at intersections have also to be considered. For example, Sun and Liu (2015) propose an eco-routing algorithm based on a signalized traffic network in which the authors use a Markov decision process to model the traffic.

To determine the energy-optimal route, heuristic searches can be implemented (Nannicini et al., 2012). Kluge et al. (2013) propose another approach as the authors solve a time-dependent eco-routing problem by using an extension of Dijkstra's algorithm.

In order to limit the computation time, eco-routing algorithms can consider a constraint on the maximum travel time or distance to reduce the set of possible solutions. Another possibility is to implement multi-objective eco-routing that minimizes not only the energy consumption but also the travel time and distance traveled. In this case, the solution proposed is a Pareto-optimal route (Bertsekas, 1995; De Nunzio et al., 2017).

5. Traffic flow control design for emission and energy consumption reduction

In Section 4, we presented vehicle-based control designs aiming at reducing the emissions and energy consumption of a single vehicle. In this section, we review some road-based control strategies to reduce the environmental impact on a large spatial scale and for a large number of vehicles. These strategies consist in regulating vehicular flow by controlling speed limits, traffic-light duty cycles or offsets, split ratios at intersections or bifurcations, or mobile actuators (e.g. autonomous vehicles). In the following, the control strategies are classified according to the employed actuator. For each actuator, we review first the strategies adapted to highways, and then the strategies that can be set up for an urban environment.

The objective of the following frameworks is to determine via an optimization method, at each control time step, the control inputs that minimize the traffic emissions and energy consumption. Note that some of the papers presented in the following do not explicitly minimize emissions or energy consumption. Instead, they tend to mitigate congestion and eliminate shock waves through density homogenization, vehicles inter-distance equalization, etc. These methods are likely to indirectly reduce emissions and energy consumption as they reduce the number of acceleration and deceleration (Barth and Boriboonsomsin, 2008). However, it is important to make careful analyses about the assessment of the effect of congestion reduction on emissions and energy consumption. In fact, their relationship depends on many factors such as the speed of the traffic (Fiori et al., 2018).

5.1. *Speed limits control*

A first approach to regulate the flow in order to reduce the emissions and energy consumption is to control speed limits. This corresponds to imposing variable location-dependent speed limits across the road network.

Many works present variable speed limits adapted to highways. Some of them do not aim at explicitly reducing emissions and energy consumption (e.g. SPECIALIST method that eliminates shock waves (Hegyi et al., 2008)). An increasingly common approach is to use reinforcement learning methods to optimize speed limits. Walraven et al. (2016) propose to follow this approach to minimize the amount of time vehicles spend on the highway under consideration.

Some other works are explicitly oriented on emissions and energy consumption reduction. Generally, they implement a multi-objective optimization that minimizes also the travel time so that unrealistic solutions like speed limits equal to zero are avoided. For example, Zu et al. (2018) express the energy consumption minimization on highways as a convex quadratic optimization problem whose objective function is derived from the average speed-based COPERT model. The density is expressed as a function of the speed, considering the Greenshields fundamental diagram (cf. Table 3). Another approach is proposed by Zegeye et al. (2012). The authors propose a control design applicable to highways in which the speed limits are determined by Model Predictive Control (MPC). Because of the non-convex nature of the objective function, Zegeye et al. (2012) use a multi-start local sequential quadratic programming method to determine the control inputs.

MPC offers opportunities for traffic control as it is compatible with the uncertainties of the traffic models, and it can also handle non-linear and non-convex optimization. However, computation times have to be reduced to make MPC tractable for real-time operation, especially when the number of control inputs is too large. Hence, in order to use MPC for macroscopic traffic control without significantly compromising the performance, Zegeye et al. (2012) propose to use a parameterized MPC, more specifically called Rolling Horizon Parameterized (RHP) control.

In RHP control, the control inputs are parameterized according to some time-profiles and the optimization focuses on the parameters. The number of parameters to optimize is smaller than the number of control inputs and the set of possible solutions is generally smaller. This results in faster computation times but also a loss of performance. For computation time issues, RHP control is more suitable for real-time application than conventional MPC, but it still may be too slow, depending on the considered system, the parameterization, and the control time step.

Note that some authors propose to use approaches based on microscopic traffic models to control variable speed limits on freeways. For example, Khondaker and Kattan (2015a) present an MPC-based approach to maximize mobility, safety and environmental benefit.

A hybrid approach proposed in Van den Berg et al. (2007) aims at controlling speed limits for mixed urban and highway networks. The authors present an MPC framework that minimizes the TTS.

In an urban environment, some works do not explicitly minimize emissions and energy consumption. For example, Tajali and Hajbabaie (2018) present an MPC framework aiming at harmonizing the speed within the network and maximizing the outflows.

Other works explicitly aim at reducing emissions and energy consumption. Taylor (2000) presents an approach to evaluate the impact of various speed limits on emissions, energy consumption, and traffic congestion, without seeking to optimize speed limits. De Nunzio et al. (2014) propose a method to find the optimal speed limit of a road section. The traffic model considered is the VLM presented in Section 3.1.2, and the same notations are used here. The control input is $v_{\max}$ and the objective function is the weighted sum of the energy consumption, the total time spent TTS, the instantaneous travel time ITT and the total travel distance TTD. These new metrics are defined as follows

$$ITT(\rho) = \frac{L-l}{v_{\max}} + \frac{l\rho^{c}}{w(\rho^{M}-\rho^{c})} \tag{63}$$

$$TTD(\rho) = T_{\text{cycle}}\left(\rho_{f} v_{\max} L + [w(\rho^{M}-\rho_{c}) - v_{\max}\rho_{f}]l\right) \tag{64}$$

$$TTS(\rho) = T_{\text{cycle}}\left(\rho_{f} L + (\rho_{c}-\rho_{f})l\right) \tag{65}$$

A method based on shock waves theory to control speed limits in an urban area has been proposed by De Nunzio and Gutman (2017) to optimize energy consumption and TTS.

Panis et al. (2006) present a methodology to analyze the environmental impact of speed limits in an urban environment. The authors use the microscopic traffic model DRACULA and a data-based emission and energy consumption model. A case study is conducted in Ghentbrugge, a neighborhood of the city of Ghent, Belgium. Similarly, Liu and Tate (2004) propose to study the effect of speed limits in an urban network by implementing Intelligent Speed Adaptation (ISA). This system suggests, or imposes, speed limits to the driver through in-vehicle electronic devices. Note that ISA only informs road users of the speed limits, but does not calculate it independently for each vehicle. In other words, it is just a communication device. In this study, the authors consider the speed limits as inputs of the simulation, i.e. they can vary with locations but are fixed over the simulation time period, and are not optimized. One may also consider dynamic speed limits based on an optimization framework. The authors use the DRACULA traffic model. One of the main limitations of this kind of approach based on microscopic traffic models is that a lot of data are involved. They are usually very difficult to obtain, and they cause long computation times.

Note that machine learning methods can be used to control variable speed limits. For example, Zhu and Ukkusuri (2014) present a Reinforcement Learning (RL) approach aiming at optimizing the total network throughput, the delay time, and the emissions. The authors propose a case study conducted on the Sioux Falls network.

A general overview of the theoretical background and the main strategies of variable speed limits strategies can be found in Khondaker and Kattan (2015b).

5.2. *Traffic lights control*

Road-based ecological control designs based on different actuators can be found in the literature. The main alternative is traffic lights control. On freeways, this control strategy, known as ramp metering, can be applied on on-ramps, and it consists in regulating the traffic flow entering the highway.

Many ramp metering strategies do not explicitly optimize emissions and energy consumption, but they aim at reaching a desired density. That is the case of ALINEA method, presented in Papageorgiou et al. (1991), which uses a feedback law and the traffic density measured downstream from the merge area. Similarly, Pisarski and Canudas-de-Wit (2016) present an approach to balance the vehicle density on the freeway by formulating the optimization problem as a non-cooperative Nash game.

Some authors express the ramp metering control approach as an optimization problem aiming at directly reducing emissions and energy consumption. For example, Csikós et al. (2011) present a multi-objective optimization based on a constrained LQ (Linear-Quadratic) control, minimizing both TTS and traffic emissions on freeways. Pasquale et al. (2015) formulate the ramp metering control problem as a multi-objective nonlinear constrained optimization problem considering the same objective function. These metrics are calculated considering both the traffic in the on-ramp and in the mainstream. The emissions are calculated using an average speed-based model based on COPERT. The nonlinear optimization problem is solved with a specific version of the feasible direction algorithm: the derivative backpropagation method RPROP. A specific feature of this work is that the authors consider two classes of vehicles (cars and trucks) individually controlled by the optimization process.

In an urban environment, many traffic signal timing optimization strategies have been developed to control traffic-light cycles. Most of them do not explicitly optimize emissions and energy consumption. Instead, they minimize the congestion by improving the throughput and reducing the delay. Some of these strategies are: SCOOT (Split, Cycle and Offset Optimisation Technique) (Hunt et al., 1981), SCATS (Sydney Coordinated Adaptive Traffic System) (Lowrie et al., 1982), RHODES (Real-time Hierarchical Optimized Distributed Effective System) (Mirchandani and Head, 2001), TUC (Traffic-responsive Urban Control) (Dinopoulou et al., 2006), max-pressure (Varaiya, 2013).

Grandinetti et al. (2018) formulate the signal timing control problem as a CTM-based real-time convex optimization whose objective function is the weighted sum of TTD, the density balancing and a regularization term that penalizes abrupt changes in the control dynamics. The density balancing term aims at homogenizing the density over the network. The algorithm is split into subproblems whose sizes are independent of the network size, thus allowing for scalability.

Some authors explicitly consider emissions and energy consumption reduction. For example, Han et al. (2016) express the signal timing optimization in an urban environment as an LTM-based Mixed Integer Linear Program (MILP) optimizing both the delays and the emissions. Emissions are calculated as a function of the density of the links, by calculating the spatial and the temporal accelerations defined in Section 3.2.2. Similarly, Osorio and Nanduri (2015) propose a meta-model that considers the simulations of TTS and fuel consumption as well as their analytical approximations to solve the urban signal timing optimization using a simulation-based optimization algorithm.

MPC can be implemented in a traffic light control framework. For example, Lin et al. (2013) present a method adapted for urban traffic networks based on MPC. The authors consider a dynamic fluid-based meta-model associating the S model and VT-micro to characterize emissions (cf. Section 3.2.2). The approach aims at reducing both congestion and emissions as the objective function considers the weighted sum of TTS and total emissions. Jamshidnejad et al. (2018) propose a similar approach based on a gradient-based optimization approach. The authors consider an extension of the S traffic model. The objective function considers the weighted sum of TTS, total emissions, and the absolute difference of two temporally successive control inputs, in order to avoid abrupt variations.

A more precise approach can be found in Stevanovic et al. (2009). The authors propose to simulate the traffic dynamics through a microscopic traffic model, namely VISSIM, and to calculate the emissions by using the CMEM emission and energy consumption model (cf. Section 2.2). A signal timings optimization is then conducted using VISGAOST, an optimization program based on the stochastic nature of genetic algorithms. Although the authors propose a case study on a road network composed of two suburban arteries, an online optimization based on this method is not possible because of lengthy calculation times. But such methods can be implemented for an offline optimization.

RL methods can also be implemented to control traffic lights in an urban network. For example, Khamis and Gomaa (2012) present a framework that considers the microscopic dynamics of vehicles. The authors propose to approximate the energy consumption metric by the average number of vehicles stops, assuming that this performance index can be directly related to ecological issues.

5.3. Coordinated speed limits and traffic lights control

To improve the results of road-based control, it is possible to coordinate actuators such as speed limits and signal timing control.

For freeways control, Hegyi et al. (2005) propose a method to optimize TTS, without considering emissions and energy consumption. The authors develop an MPC framework, in which the control inputs are speed limits and ramp metering.

Other authors have used coordinated speed limits and signal timing control to reduce emissions and energy consumption. For example, Zegeye (2011) optimizes TTS, fuel consumption, and NOx emissions via MPC. A very similar approach is presented in Liu et al. (2017). The authors also use MPC to control both ramp metering and speed limits on a highway section, and the objective function is the weighted sum of TTS and total emissions. A specific feature of this work is that multiple classes of vehicles are considered.

A problem to study in an urban environment is bandwidth maximization along an artery. Assuming that all the traffic lights have a common cycle, the problem of bandwidth maximization consist in maximizing the vehicle throughput along the artery under study, by traffic lights offset control. Usually, the actuators are only the traffic lights offset, like presented in Mehr et al. (2018) in which the authors express a nonlinear optimization problem and convert it to a MILP. The bandwidth maximization problem optimizes the flow of vehicles but does not explicitly reduce the emissions and energy consumption. Therefore, De Nunzio et al. (2015) propose a formulation as an optimization problem in which the objective function contains also terms approximating TTS and energy consumption. In this work, the authors use coordinated actuators, namely speed limits and signal timing controls. None of the bandwidth maximization strategies presented is based on a traffic model. Hence, they work best in steady-state under-saturated traffic conditions.

5.4. Dynamic routing

Another solution to reduce emissions and energy consumption is to use dynamic routing. This method consists in redistributing the traffic demand over the network in a more efficient way by controlling the split ratios. In practice, the controller predicts the optimal routes for the main traffic flow directions, and the associated recommendations are communicated to the road users by the mean of in-vehicle devices, radio, or variable message signs (Treiber and Kesting, 2013a).

In the literature, the control objective of dynamic routing problems is usually to reach system-optimum or user-equilibrium. The system-optimum corresponds to the minimum TTS and the user-equilibrium is characterized by a density distribution for which all used routes between the same origin-destination pair have the same travel time (Xu et al., 2011).

Dynamic routing could also be used to directly reduce emissions and energy consumption. For example, Luo et al. (2016)

propose a real-time en-route diversion control strategy that minimizes TTS, total emissions and fuel consumption. The route recommendation provided by variable message signs is considered as the control variable. The split ratios are calculated from the route recommendation considering a drivers' compliance rate which is supposed to be known. The route diversion control uses MPC based on a parallel Tabu Search algorithm.

Emission pricing can also be used as a dynamic routing method aiming at influencing route selection in order to reduce emissions and energy consumption. This method can be static or dynamic. Dynamic road pricing studies based on emissions and energy consumption are reviewed in Wang et al. (2018).

5.5. Mobile actuators

Most of the strategies presented above are motionless in the sense that traffic lights, ramp metering, message signs and speed limit signs exert commands at a fixed location. A new approach is to consider mobile actuators, namely vehicles that could be controlled to have an impact on the surrounding traffic. Typically, this corresponds to the injection of some autonomous vehicles in the traffic flow with the objective of stabilizing it.

Stern et al. (2019) present how this method can reduce the emissions of the whole traffic by dampening stop-and-go waves. To validate this approach, the authors present the results of field experiments in which vehicle velocity and acceleration data are collected. These experiments use a single autonomous vehicle to dampen traffic waves on a ring road with 20 other human-piloted vehicles. The results are coherent with the simulations of Wu et al. (2018). Yang and Jin (2014) present a similar control based on inter-vehicle communication.

Autonomous vehicles present opportunities in terms of traffic stabilization, emissions, and energy consumption. They also induce a smoother driving and fewer braking events. But the results presented in Stern et al. (2019) hold for situations with traffic waves only.

A country-level evaluation of the impact of autonomous vehicles on the environment can be found in Liu et al. (2019). The authors consider different scenarios regarding the autonomous vehicle penetration rate by 2050.

6. Conclusion and outlook

The current situation regarding pollutant emissions and energy consumption of road transportation is alarming both for environmental and health reasons. Ecological traffic management appears to be a promising lever in the long-term to reduce the environmental impact of transportation.

This paper surveys the existing emission and energy consumption models, as well as the traffic control strategies to reduce them, either by considering vehicles independently, or by considering traffic flows. The main advantages and drawbacks of the different approaches are highlighted.

The first step to estimate emissions and energy consumption is to measure, or simulate, the kinematics of vehicles, that can be either static or dynamic. Traffic models can be implemented on a microscopic or macroscopic scale. The complexity of large scale road networks is essentially due to the processing of junctions, and the choice of temporal and spatial discretizations, which represent a crucial point.

From the traffic kinematics, emissions and energy consumption can be estimated using either data or physics-based approaches. Thus, many associations of models are possible. For complexity reasons, some are more suitable than others. In order to go large scale, the objective is to find a balance between accuracy and computation time, which depends mainly on the use of the framework (e.g. compatibility with control methods). For example, a question is whether the additional complexity introduced by a second-order traffic model significantly improves the accuracy of a first order model in depicting the traffic behaviors that impact energy efficiency. Similarly, a microscopic approach to describe large-scale emissions and energy consumption would provide the best estimations but it would involve a lot of data that can be difficult to obtain and process, the need to precisely calibrate the model, and a sharp increase in computation times. However, this approach can be useful for offline validation purposes.

Traffic management can be carried out by controlling a single vehicle to reduce its emissions and energy consumption, or by acting on a large spatial scale with actuators such as speed limits, traffic lights, dynamic routing or autonomous vehicles. Usually, a multi-objective optimization is considered to control the traffic with ecological concerns in order to ensure realistic solutions.

Many articles propose traffic control designs that do not aim at reducing emissions and energy consumption but more classic metrics such as the distance traveled, the delays or the total time spent in the networks. These methods can be adapted to multi-objective control problems considering ecological issues, which offers promising opportunities in this research field. Also, note that some control designs aiming at improving traffic fluidity can have a positive impact on environmental metrics as they reduce the number of stops and accelerations.

Some clear trends can be identified in the ecological approach of traffic control. For example, autonomous vehicles are considered the next major technological advance in the transport sector. Not only do they have an important role to play in road safety, but they can also reduce the impact of transport on the environment by reducing vehicle ownership and improving energy consumption rate (Liu et al., 2019). However, at system-wide level, the effect of autonomous vehicles on travel demand and energy efficiency is very uncertain and might increase the total fuel consumption (Brown et al., 2014; U.S. Department of Energy, 2018). Autonomous vehicles are a lever able to influence and regulate the surrounding traffic. Analyses of the best penetration rate of connected and automated vehicles in freeway traffic to improve global energy performance are recently appearing (Rios-Torres and Malikopoulos, 2018), and further exploration of the effects in an urban environment should be conducted.

Connected vehicles able to communicate with the infrastructure are also expected to become more numerous, which would considerably increase the available data. Moreover, computing capabilities have recently been greatly improved. These aspects are expected to improve the efficiency of control strategies and make microscopic approaches a more interesting option.

Machine learning methods are also a major trend both for estimation and reduction purposes of emissions and energy consumption. Neural networks are becoming more and more precise to estimate emissions and energy consumption from vehicle operating variables. They are a good alternative to physics-based approaches because of the high non-linearity of emissions and energy consumption. RL approaches are an important trend in traffic control. They can be implemented considering different actuator types.

MPC seems to be very popular among traffic control methods as it is compatible with the uncertainties of the traffic models, and it can also handle non-linear and non-convex optimization.

Some gaps can be identified concerning the ecological approach of traffic control. One of them is that obtaining large-scale data is difficult because most vehicles are still not fully connected. The issue of missing data imputation has been addressed by some authors (Qu et al., 2009).

Moreover, experiments in traffic control are very long and expensive to put in place. Hence, most approaches are not validated by real experimentation. However, more and more cities are taking action to reduce pollutant emissions. For example, many cities are generalizing the speed limit to 30 km/h in most streets (Bordarie, 2017). Similarly, old diesel vehicles are being banned from many large cities, especially in Germany (Möhner, 2018). These strong measures could be associated with a dynamic control of traffic aiming at explicitly reducing emissions and energy consumption.

Another identified gap is that models intended for large-scale control purposes are limited by computation time. A major issue is their level of detail (e.g. approximation of the acceleration of macroscopic traffic models, processing of junctions in road networks). This determines the compromise between accuracy and computation time, which inevitably leads to approximations. In a hypothetical future in which many vehicles would be connected or autonomous, the question of data processing from a computational point of view for control purposes would also certainly arise.

Concerning control strategies, a moot point is to find the metric to optimize along with the ecological issues. Depending on the objective, many approaches are possible (e.g. minimize the travel duration or distance, homogenize the density or the speed).

An interesting aspect to study would be the impact of traffic congestion on emissions and energy consumption. For example, it could be interesting to analyze in detail the most impacting traffic phenomena on emissions and energy consumption.

The best models for emission and energy consumption reduction for large-scale road networks are probably yet to be found. To control the traffic with ecological concerns, one may explore the use of new actuators, or coordinate them at a large spatial scale.

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References

Aboudolas, K., Papageorgiou, M., and Kosmatopoulos, E. (2009). Store-and-forward based methods for the signal control problem in large-scale congested urban road networks. *Transportation Research Part C: Emerging Technologies*, 17(2):163 – 174.

Ahn, K. (1998). Microscopic fuel consumption and emission modeling. Master's thesis, Virginia Tech.

Ahn, K. and Rakha, H. (2008). The effects of route choice decisions on vehicle energy consumption and emissions. *Transportation Research Part D: Transport and Environment*, 13(3):151 – 167.

Ahn, K., Rakha, H., and Trani, A. (2004). Microframework for modeling of high-emitting vehicles. *Transportation Research Record*, 1880:39–49.

Alsabaan, M., Naik, K., Khalifa, T., and Nayak, A. (2012). Applying vehicular networks for reduced vehicle fuel consumption and co2 emissions. In *Intelligent Transportation Systems*. IntechOpen.

An, F., Barth, M., Norbeck, J., and Ross, M. (1997). Development of comprehensive modal emissions model: Operating under hot-stabilized conditions. *Transportation Research Record: Journal of the Transportation Research Board*, (1587):52–62.

Andersen, O., Jensen, C. S., Torp, K., and Yang, B. (2013). Ecotour: Reducing the environmental footprint of vehicles using eco-routes. In *Mobile Data Management (MDM), 2013 IEEE 14th International Conference on*, volume 1, pages 338–340. IEEE.

Andre, M. and Pronello, C. (1997). Relative influence of acceleration and speed on emissions under actual driving conditions. *International Journal of Vehicle Design*, 18(3–4):340–353.

Aw, A. and Rascle, M. (2000). Resurrection of" second order" models of traffic flow. *SIAM Journal on Applied Mathematics*, 60(3):916–938.

Barth, M., An, F., Norbeck, J., and Ross, M. (1996). Modal emissions modeling: A physical approach. *Transportation Research Record: Journal of the Transportation Research Board*, (1520):81–88.

Barth, M. and Boriboonsomsin, K. (2008). Real-world carbon dioxide impacts of traffic congestion. *Transportation Research Record: Journal of the Transportation Research Board*, (2058):163–171.

Bertsekas, D. P. (1995). *Dynamic programming and optimal control*, volume 1. Athena scientific Belmont, MA.

Boehme, T., Held, F., Rollinger, C., Rabba, H., Schultalbers, M., and Lampe, B. (2013). Application of an optimal control problem to a trip-based energy management for electric vehicles. *SAE International Journal of Alternative Powertrains*, 2:115–126.

Bordarie, J. (2017). Public policy of urban mobility: Impact of the history and practices on young drivers' social representation of 30 km/h. *Journal of Nonprofit & Public Sector Marketing*, 29(2):211–234.

Boriboonsomsin, K., Barth, M. J., Zhu, W., and Vu, A. (2012). Eco-routing navigation system based on multisource historical and real-time traffic information. *IEEE Transactions on Intelligent Transportation Systems*, 13(4):1694–1704.

Brown, A., Gonder, J., and Repac, B. (2014). An analysis of possible energy impacts of automated vehicles. In Meyer, G. and Beiker, S., editors, *Road vehicle automation*, Lecture notes in mobility, pages 137–153. Springer, Cham.

Burghout, W. (2004). *Hybrid microscopic-mesoscopic traffic simulation*. PhD thesis, KTH.

Canudas-de-Wit, C. (2011). Best-effort highway traffic congestion control via variable speed limits. In *Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference on*, pages 5959–5964. IEEE.

Canudas-de-Wit, C. and Ferrara, A. (2018). A variable-length cell transmission model for road traffic systems. *Transportation Research Part C: Emerging Technologies*, 97:428 – 455.

Chapman, L. (2007). Transport and climate change: a review. *Journal of Transport Geography*, 15(5):354–367.

Colombo, R. M. (2002). Hyperbolic phase transitions in traffic flow. *SIAM Journal on Applied Mathematics*, 63(2):708–721.

Csikós, A., Luspay, T., and Varga, I. (2011). Modeling and optimal control of travel times and traffic emission on freeways. *IFAC Proceedings Volumes*, 44(1):13058 – 13063. 18th IFAC World Congress.

Daganzo, C. F. (1994). The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory. *Transportation Research Part B: Methodological*, 28(4):269–287.

Daganzo, C. F. (1995). Requiem for second-order fluid approximations of traffic flow. *Transportation Research Part B: Methodological*, 29(4):277–286.

De Nunzio, G., Canudas-de-Wit, C., and Moulin, P. (2014). Urban traffic eco-driving: A macroscopic steady-state analysis. In *Control Conference (ECC), 2014 European*, pages 2581–2587. IEEE.

De Nunzio, G., Canudas-de-Wit, C., Moulin, P., and Di Domenico, D. (2016). Eco-driving in urban traffic networks using traffic signals information. *International Journal of Robust and Nonlinear Control*, 26(6):1307–1324.

De Nunzio, G., Gomes, G., Canudas-de-Wit, C., Horowitz, R., and Moulin, P. (2015). Arterial bandwidth maximization via signal offsets and variable speed limits control. In *Decision and Control (CDC), 2015 IEEE 54th Annual Conference on*, pages 5142–5148. IEEE.

De Nunzio, G. and Gutman, P.-O. (2017). An application of shock wave theory to urban traffic control via dynamic speed advisory. In *hEART 2017: 6th Symposium of the European Association for Research in Transportation*.

De Nunzio, G., Thibault, L., and Sciarretta, A. (2017). Bi-objective eco-routing in large urban road networks. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–7.

Dib, W., Chasse, A., Di Domenico, D., Moulin, P., and Sciarretta, A. (2012). Evaluation of the energy efficiency of a fleet of electric vehicle for eco-driving application. *Oil & Gas Science and Technology–Revue d'IFP Energies nouvelles*, 67(4):589–599.

Dimitrakopoulos, G. and Demestichas, P. (2010). Intelligent transportation systems. *IEEE Vehicular Technology Magazine*, 5(1):77–84.

Dinopoulou, V., Diakaki, C., and Papageorgiou, M. (2006). Applications of the urban traffic control strategy tuc. *European Journal of Operational Research*, 175(3):1652 – 1665.

Ericsson, E., Larsson, H., and Brundell-Freij, K. (2006). Optimizing route choice for lowest fuel consumption – potential effects of a new driver support tool. *Transportation Research Part C: Emerging Technologies*, 14(6):369 – 383.

Ferrara, A., Sacone, S., and Siri, S. (2018a). First-order macroscopic traffic models. In *Freeway traffic modelling and control*, chapter 3. Springer.

Ferrara, A., Sacone, S., and Siri, S. (2018b). Microscopic and mesoscopic traffic models. In *Freeway traffic modelling and control*, chapter 5. Springer.

Ferrara, A., Sacone, S., and Siri, S. (2018c). Second-order macroscopic traffic models. In *Freeway traffic modelling and control*, chapter 4. Springer.

Fiori, C., Arcidiacono, V., Fontaras, G., Komnos, D., Makridis, M., Marzano, V., Mattas, K., Thiel, C., and Ciuffo, B. (2018). Less congestion implies less energy consumption: Is it really true? Technical report.

Frey, H. C. and Zheng, J. (2002). Probabilistic analysis of driving cycle-based highway vehicle emission factors. *Environmental Science & Technology*, 36(23):5184–5191.

Garavello, M., Han, K., and Piccoli, B. (2016). *Models for Vehicular Traffic on Networks*. American Institute of Mathematical Sciences.

Gärtner, U., Hohenberg, G., Daudel, H., and Oelschlegel, H. (2004). Development and application of a semi-empirical nox model to various hd diesel engines. In *Thermo-and Fluid Dynamic Processes in Diesel Engines 2*, pages 285–312. Springer.

Gazis, D. C. and Potts, R. B. (1963). The oversaturated intersection. Technical report.

Grandinetti, P., Canudas-de Wit, C., and Garin, F. (2018). Distributed optimal traffic lights design for large-scale urban networks. *IEEE Transactions on Control Systems Technology*, (99):1–14.

Greenberg, H. (1959). An analysis of traffic flow. *Operations Research*, 7(1):79–85.

Greenshields, B., Channing, W., Miller, H., et al. (1935). A study of traffic capacity. In *Highway research board proceedings*, volume 1935. National Research Council (USA), Highway Research Board.

Guanetti, J., Kim, Y., and Borrelli, F. (2018). Control of connected and automated vehicles: State of the art and future challenges. *Annual Reviews in Control*.

Hall, R. (2012). *Handbook of transportation science*, volume 23. Springer Science & Business Media.

Han, J., Sciarretta, A., Ojeda, L. L., De Nunzio, G., and Thibault, L. (2018). Safe-and eco-driving control for connected and automated electric vehicles using analytical state-constrained optimal solution. *IEEE Transactions on Intelligent Vehicles*, 3(2):163–172.

Han, K., Liu, H., Gayah, V. V., Friesz, T. L., and Yao, T. (2016). A robust optimization approach for dynamic traffic signal control with emission considerations. *Transportation Research Part C: Emerging Technologies*, 70:3–26.

Hausberger, S. (2009). Emission factors from the model phem for the hbefa version 3.

Hegyi, A., Hoogendoorn, S. P., Schreuder, M., Stoelhorst, H., and Viti, F. (2008). Specialist: A dynamic speed limit control algorithm based on shock wave theory. In *2008 11th International IEEE Conference on Intelligent Transportation Systems*, pages 827–832.

Hegyi, A., Schutter, B. D., and Hellendoorn, H. (2005). Model predictive control for optimal coordination of ramp metering and variable speed limits. *Transportation Research Part C: Emerging Technologies*, 13(3):185 – 209.

Helbing, D. (1995). Improved fluid-dynamic model for vehicular traffic. *Physical Review E*, 51(4):3164.

Hellström, E., Ivarsson, M., Åslund, J., and Nielsen, L. (2009). Look-ahead control for heavy trucks to minimize trip time and fuel consumption. *Control Engineering Practice*, 17(2):245–254.

Herty, M. and Rascle, M. (2006). Coupling conditions for a class of second-order models for traffic flow. *SIAM Journal on Mathematical Analysis*, 38(2):595–616.

HomChaudhuri, B., Vahidi, A., and Pisu, P. (2017). Fast model predictive control-based fuel efficient control strategy for a group of connected vehicles in urban road conditions. *IEEE Transactions on Control Systems Technology*, 25(2):760–767.

Hoogendoorn, S. P. and Bovy, P. H. (2001). State-of-the-art of vehicular traffic flow modelling. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 215(4):283–303.

Hunt, P., Robertson, D., Bretherton, R., and Winton, R. (1981). Scoot-a traffic responsive method of coordinating signals. Technical report.

International Energy Agency (2018). World energy outlook 2018.

Jafarmadar, S. (2015). A comparative analysis of two neural network predictions for performance and emissions in a biodiesel fuelled diesel engine.

Jamshidnejad, A., Papamichail, I., Papageorgiou, M., and De Schutter, B. (2017). A mesoscopic integrated urban traffic flow-emission model. *Transportation Research Part C: Emerging Technologies*, 75:45–83.

Jamshidnejad, A., Papamichail, I., Papageorgiou, M., and De Schutter, B. (2018). Sustainable model-predictive control in urban traffic networks: Efficient solution based on general smoothening methods. *IEEE Transactions on Control Systems Technology*, 26(3):813–827.

Jie, L., Zuylen, H. V., Chen, Y., Viti, F., and Wilmink, I. (2013). Calibration of a microscopic simulation model for emission calculation. *Transportation Research Part C: Emerging Technologies*, 31:172 – 184.

Jurik, T., Cela, A., Hamouche, R., Natowicz, R., Reama, A., Niculescu, S., and Julien, J. (2014). Energy optimal real-time navigation system. *IEEE Intelligent Transportation Systems Magazine*, 6(3):66–79.

Karbowski, D., Kim, N., and Rousseau, A. (2014). Route-based online energy management of a phev and sensitivity to trip prediction. In *Vehicle Power and Propulsion Conference (VPPC), 2014 IEEE*, pages 1–6. IEEE.

Kerner, B. S. and Konhäuser, P. (1993). Cluster effect in initially homogeneous traffic flow. *Physical Review E*, 48(4):R2335.

Khamis, M. A. and Gomaa, W. (2012). Enhanced multiagent multi-objective reinforcement learning for urban traffic light control. In *2012 11th International Conference on Machine Learning and Applications*, volume 1, pages 586–591. IEEE.

Khondaker, B. and Kattan, L. (2015a). Variable speed limit: a microscopic analysis in a connected vehicle environment. *Transportation Research Part C: Emerging Technologies*, 58:146 – 159.

Khondaker, B. and Kattan, L. (2015b). Variable speed limit: an overview. *Transportation Letters*, 7.

Kluge, S., Santa, C., Dangl, S., Wild, S., Brokate, M., Reif, K., and Busch, F. (2013). On the computation of the energy-optimal route dependent on the traffic load in ingolstadt. *Transportation Research Part C: Emerging Technologies*, 36:97 – 115.

Kubička, M., Klusáček, J., Sciarretta, A., Cela, A., Mounier, H., Thibault, L., and Niculescu, S.-I. (2016). Performance of current eco-routing methods. In *Intelligent Vehicles Symposium (IV), 2016 IEEE*, pages 472–477. IEEE.

Lejri, D., Can, A., Schiper, N., and Leclercq, L. (2018). Accounting for traffic speed dynamics when calculating copert and phem pollutant emissions at the urban scale. *Transportation Research Part D: Transport and Environment*, 63:588 – 603.

Lelouvier, A., Guanetti, J., and Borrelli, F. (2017). Eco-platooning of autonomous electrical vehicles using distributed model predictive control. *Parameters*, 2:4.

Lighthill, M. J. and Whitham, G. B. (1955). On kinematic waves ii. a theory of traffic flow on long crowded roads. *Proceedings of the Royal Society London A*, 229(1178):317–345.

Lin, S., De Schutter, B., Xi, Y., and Hellendoorn, H. (2012). Efficient network-wide model-based predictive control for urban traffic networks. *Transportation Research Part C: Emerging Technologies*, 24:122–140.

Lin, S., De Schutter, B., Xi, Y., and Hellendoorn, H. (2013). Integrated urban traffic control for the reduction of travel delays and emissions. *IEEE Transactions on Intelligent Transportation Systems*, 14(4):1609–1619.

Lin, S. and Xi, Y. (2008). An efficient model for urban traffic network control. *IFAC Proceedings Volumes*, 41(2):14066–14071.

Liu, F., Zhao, F., Liu, Z., and Hao, H. (2019). Can autonomous vehicle reduce greenhouse gas emissions? a country-level evaluation. *Energy Policy*, 132:462 – 473.

Liu, R. and Tate, J. (2004). Network effects of intelligent speed adaptation systems. *Transportation*, 31(3):297–325.

Liu, S., Hellendoorn, H., and De Schutter, B. (2017). Model predictive control for freeway networks based on multi-class traffic flow and emission models. *IEEE Transactions on Intelligent Transportation Systems*, 18(2):306–320.

Lowrie, P. et al. (1982). The sydney co-ordinated adaptive traffic system (scats) – principles, methodology, algorithms. In *Proceedings of the International Conference on Road Traffic Signaling, London, UK*.

Luo, L., Ge, Y.-E., Zhang, F., and Ban, X. J. (2016). Real-time route diversion control in a model predictive control framework with multiple objectives: Traffic efficiency, emission reduction and fuel economy. *Transportation Research Part D: Transport and Environment*, 48:332–356.

Mahler, G. and Vahidi, A. (2012). Reducing idling at red lights based on probabilistic prediction of traffic signal timings. In *American Control Conference (ACC), 2012*, pages 6557–6562. IEEE.

Mandl, N. and Pinterits, M. (2018). Annual european union greenhouse gas inventory 1990–2016 and inventory report 2018.

Mehr, N., Sanselme, M., Orr, N., Horowitz, R., and Gomes, G. (2018). Offset selection for bandwidth maximization on multiple routes. In *2018 Annual American Control Conference (ACC)*, pages 6366–6371. IEEE.

Messmer, A. and Papageorgiou, M. (1990). Metanet: a macroscopic simulation program for motorway networks. *Traffic Engineering & Control*, 31:466–470.

Mirchandani, P. and Head, L. (2001). A real-time traffic signal control system: architecture, algorithms, and analysis. *Transportation Research Part C: Emerging Technologies*, 9(6):415 – 432.

Miyatake, M., Kuriyama, M., and Takeda, Y. (2011). Theoretical study on eco-driving technique for an electric vehicle considering traffic signals. In *Power Electronics and Drive Systems (PEDS), 2011 IEEE Ninth International Conference on*, pages 733–738. IEEE.

Möhner, M. (2018). Driving ban for diesel-powered vehicles in major cities: an appropriate penalty for exceeding the limit value for nitrogen dioxide?

Nannicini, G., Delling, D., Schultes, D., and Liberti, L. (2012). Bidirectional a* search on time-dependent road networks. *Networks*, 59(2):240–251.

Negrenti, E. (1999). The 'corrected average speed' approach in enea's tee model: an innovative solution for the evaluation of the energetic and environmental impacts of urban transport policies. *Science of the total environment*, 235(1-3):411–413.

Newell, G. F. (1993). A simplified theory of kinematic waves in highway traffic, part i: General theory. *Transportation Research Part B: Methodological*, 27(4):281–287.

Ntziachristos, L., Gkatzoflias, D., Kouridis, C., and Samaras, Z. (2009). Copert: A european road transport emission inventory model. pages 491–504.

Obodeh, O. and Ajuwa, C. (2009). Evaluation of artificial neural network performance in predicting diesel engine nox emissions. *European Journal of Scientific Research*, 33(4):642–653.

Osorio, C. and Nanduri, K. (2015). Energy-efficient urban traffic management: a microscopic simulation-based approach. *Transportation Science*, 49(3):637–651.

Ozatay, E., Onori, S., Wollaeger, J., Özgüner, Ü., Rizzoni, G., Filev, D., Michelini, J., and Cairano, S. D. (2014a). Cloud-based velocity profile optimization for everyday driving: A dynamic-programming-based solution. *IEEE Transactions on Intelligent Transportation Systems*, 15:2491–2505.

Ozatay, E., Ozguner, U., Michelini, J., and Filev, D. (2014b). Analytical solution to the minimum energy consumption based velocity profile optimization problem with variable road grade. *IFAC Proceedings Volumes*, 47(3):7541–7546.

Panis, L. I., Broekx, S., and Liu, R. (2006). Modelling instantaneous traffic emission and the influence of traffic speed limits. *Science of the Total Environment*, 371(1-3):270–285.

Papageorgiou, M., Hadj-Salem, H., Blosseville, J.-M., et al. (1991). Alinea: A local feedback control law for on-ramp metering. *Transportation Research Record*, 1320(1):58–67.

Pasquale, C., Papamichail, I., Roncoli, C., Sacone, S., Siri, S., and Papageorgiou, M. (2015). Two-class freeway traffic regulation to reduce congestion and emissions via nonlinear optimal control. *Transportation Research Part C: Emerging Technologies*, 55:85–99.

Payne, H. (1971). Models of freeway traffic and control. In *Mathematical Models of Public Systems*. Simul. Counc. Proc.

Pelkmans, L. and Debal, P. (2006). Comparison of on-road emissions with emissions measured on chassis dynamometer test cycles. *Transportation Research Part D: Transport and Environment*, 11(4):233 – 241.

Piccoli, B. and Tosin, A. (2009). A review of continuum mathematical models of vehicular traffic. *Encyclopedia of Complexity and Systems Science*, pages 9727–9749.

Pisarski, D. and Canudas-de-Wit, C. (2016). Nash game-based distributed control design for balancing traffic density over freeway networks. *IEEE Transactions on Control of Network Systems*, 3(2):149–161.

Post, K., Kent, J., Tomlin, J., and Carruthers, N. (1984). Fuel consumption and emission modelling by power demand and a comparison with other models. *Transportation Research Part A: General*, 18(3):191–213.

Qi, Y. G., Teng, H. H., and Yu, L. (2004). Microscale emission models incorporating acceleration and deceleration. *Journal of Transportation Engineering*, 130(3):348–359.

Qu, L., Li, L., Zhang, Y., and Hu, J. (2009). Ppca-based missing data imputation for traffic flow volume: A systematical approach. *IEEE Transactions on Intelligent Transportation Systems*, 10(3):512–522.

Rai, N. K., Vyas, A., and Singh, S. K. (2017). Street level modeling of pollutants for residential areas. *International Journal of Engineering Research and Application*, 7(10):52–57.

Rakha, H., Ahn, K., and Trani, A. (2003). Comparison of mobile5a, mobile6, vt-micro, and cmem models for estimating hot-stabilized light-duty gasoline vehicle emissions. *Canadian Journal of Civil Engineering*, 30:1010–1021.

Richards, P. I. (1956). Shock waves on the highway. *Operations Research*, 4(1):42–51.

Rios-Torres, J. and Malikopoulos, A. A. (2018). Impact of partial penetrations of connected and automated vehicles on fuel consumption and traffic flow. *IEEE Transactions on Intelligent Vehicles*, 3(4):453–462.

Schiper, N. (2017). *Traffic data sampling for air pollution estimation at different urban scales*. PhD thesis, Université de Lyon.

Sciarretta, A., Nunzio, G. D., and Ojeda, L. L. (2015). Optimal ecodriving control: Energy-efficient driving of road vehicles as an optimal control problem. *IEEE Control Systems Magazine*, 35(5):71–90.

Scora, G. and Barth, M. (2006). Comprehensive modal emissions model (cmem), version 3.01. *User guide. Centre for Environmental Research and Technology. University of California, Riverside*, 1070.

Seredynski, M., Mazurczyk, W., and Khadraoui, D. (2013). Multi-segment green light optimal speed advisory. In *Parallel and Distributed Processing Symposium Workshops & PhD Forum (IPDPSW), 2013 IEEE 27th International*, pages 459–465. IEEE.

Sobrino, N., Monzón, A., and Hernandez, S. (2014). Reduced carbon and energy footprint in highway operations: The highway energy assessment (hera) methodology. *Netw Spat Econ*, 16:1–20.

Stern, R. E., Chen, Y., Churchill, M., Wu, F., Monache, M. L. D., Piccoli, B., Seibold, B., Sprinkle, J., and Work, D. B. (2019). Quantifying air quality benefits resulting from few autonomous vehicles stabilizing traffic. *Transportation Research Part D: Transport and Environment*, 67:351 – 365.

Stevanovic, A., Stevanovic, J., Zhang, K., and Batterman, S. (2009). Optimizing traffic control to reduce fuel consumption and vehicular emissions: Integrated approach with vissim, cmem, and visgaost. *Transportation Research Record*, 2128(1):105–113.

Sturm, P., Kirchweger, G., Hausberger, S., and Almbauer, R. (1998). Instantaneous emission data and their use in estimating road traffic emissions. *International Journal of Vehicle Design*, 20.

Sun, C., Guanetti, J., Borrelli, F., and Moura, S. (2018). Robust eco-driving control of autonomous vehicles connected to traffic lights. *arXiv preprint arXiv:1802.05815*.

Sun, J. and Liu, H. X. (2015). Stochastic eco-routing in a signalized traffic network. *Transportation Research Part C: Emerging Technologies*, 59:32 – 47. Special Issue on International Symposium on Transportation and Traffic Theory.

Tajali, M. and Hajbabaie, A. (2018). Dynamic speed harmonization in urban street networks. *Computer-Aided Civil and Infrastructure Engineering*.

Tampère, C. M., Corthout, R., Cattrysse, D., and Immers, L. H. (2011). A generic class of first order node models for dynamic macroscopic simulation of traffic flows. *Transportation Research Part B: Methodological*, 45(1):289 – 309.

Taylor, M. (2000). Network modeling of the traffic, environmental and energy effects of lower urban speed limits. *Road and Transport Research*, 9:48–57.

Thibault, L., Degeilh, P., Lepreux, O., Voise, L., Alix, G., and Corde, G. (2016). A new gps-based method to estimate real driving emissions. In *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, pages 1628–1633.

Transport & Environment (2018). Co2 emissions from cars: the facts.

Treiber, M. and Kesting, A. (2013a). Model-based traffic flow optimization. In *Traffic Flow Dynamics*, chapter 21. Springer.

Treiber, M. and Kesting, A. (2013b). Trajectory and floating-car data. In *Traffic Flow Dynamics*, chapter 2. Springer.

U.S. Department of Energy (2018). Autonomous vehicles: Uncertainties and energy implications.

U.S. Energy Information Administration (2017a). International energy outlook.

U.S. Energy Information Administration (2017b). Study of the potential energy consumption impacts of connected and automated vehicles.

Van den Berg, M., Hegyi, A., De Schutter, B., and Hellendoorn, H. (2007). Integrated traffic control for mixed urban and freeway networks: A model predictive control approach. *European Journal of Transport and Infrastructure Research EJTIR, 7 (3)*.

van Wageningen-Kessels, F., van Lint, H., Vuik, K., and Hoogendoorn, S. (2015). Genealogy of traffic flow models. *EURO Journal on Transportation and Logistics*, 4(4):445–473.

Varaiya, P. (2013). The max-pressure controller for arbitrary networks of signalized intersections. In *Advances in Dynamic Network Modeling in Complex Transportation Systems*, pages 27–66. Springer.

Vreeswijk, J. D., Mahmod, M., and van Arem, B. (2013). Energy efficient traffic management and control - the ecomove approach and expected benefits. In *13th International IEEE Conference on Intelligent Transportation Systems*, pages 955–961.

Walraven, E., Spaan, M. T., and Bakker, B. (2016). Traffic flow optimization: a reinforcement learning approach. *Engineering Applications of Artificial Intelligence*, 52:203 – 212.

Wang, Y., Szeto, W. Y., Han, K., and Friesz, T. L. (2018). Dynamic traffic assignment: A review of the methodological advances for environmentally sustainable road transportation applications. *Transportation Research Part B: Methodological*, 111:370–394.

Whitham, G. B. (1974). *Linear and nonlinear waves*. John Wiley & Sons.

World Health Organization (2016). Ambient air pollution: a global assessment of exposure and burden of disease.

Wu, C., Bayen, A. M., and Mehta, A. (2018). Stabilizing traffic with autonomous vehicles. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1–7. IEEE.

Wu, G., Boriboonsomsin, K., and Barth, M. J. (2014). Development and evaluation of an intelligent energy-management strategy for plug-in hybrid electric vehicles. *IEEE Trans. Intelligent Transportation Systems*, 15(3):1091–1100.

Xie, B., Xu, M., Härri, J., and Chen, Y. (2013). A traffic light extension to cell transmission model for estimating urban traffic jam. In *PIMRC*, pages 2566–2570.

Xu, T. D., Sun, L. J., Peng, Z. R., and Hao, Y. (2011). Integrated route guidance and ramp metering consistent with drivers' en-route diversion behaviour. *IET Intelligent Transport Systems*, 5(4):267–276.

Xu, Z., Kang, Y., and Lv, W. (2017). Analysis and prediction of vehicle exhaust emission using ann. In *2017 36th Chinese Control Conference (CCC)*, pages 4029–4033. IEEE.

Yang, H. and Jin, W.-L. (2014). A control theoretic formulation of green driving strategies based on inter-vehicle communications. *Transportation Research Part C: Emerging Technologies*, 41:48–60.

Yperman, I. (2007). The link transmission model for dynamic network loading.

Zegeye, S., De Schutter, B., Hellendoorn, J., Breunesse, E., and Hegyi, A. (2013). Integrated macroscopic traffic flow, emission, and fuel consumption model for control purposes. *Transportation Research Part C: Emerging Technologies*, 31:158–171.

Zegeye, S. K. (2011). Model-based traffic control for sustainable mobility.

Zegeye, S. K., De Schutter, B., Hellendoorn, J., Breunesse, E. A., and Hegyi, A. (2012). A predictive traffic controller for sustainable mobility using parameterized control policies. *IEEE Transactions on Intelligent Transportation Systems*, 13(3):1420–1429.

Zhang, H. M. (2002). A non-equilibrium traffic model devoid of gas-like behavior. *Transportation Research Part B: Methodological*, 36(3):275–290.

Zhang, Y. and Cassandras, C. G. (2018). The penetration effect of connected automated vehicles in urban traffic: An energy impact study. *arXiv preprint arXiv:1803.05577*.

Zhu, F. and Ukkusuri, S. V. (2014). Accounting for dynamic speed limit control in a stochastic traffic environment: A reinforcement learning approach. *Transportation Research Part C: Emerging Technologies*, 41:30 – 47.

Zu, Y., Liu, C., Dai, R., Sharma, A., and Dong, J. (2018). Real-time energy-efficient traffic control via convex optimization. *Transportation Research Part C: Emerging Technologies*, 92:119 – 136.